Impossible Probability:

Anthology,

Vol 6.

I doubt, therefore I exist.

Dr Ruben Garcia Pedraza

Preliminary Words for the Publication of *Impossible Probability, Anthology*, in Spanish:

Impossible Probability

The work presented here is a compilation of the posts I published on the blog *Impossible Probability* between 1 August 2011 and 13 January 2018, the posts I wrote in Spanish. From 13 January onwards, while living and working in London in different schools, and given the importance we already knew Global Artificial Intelligence was going to have, I would try to write them in English with the help of online correctors and translators, especially Google, and later I would use Grammarly.

The originals written in English, with all their imperfections, are still preserved on the *Impossible Probability* blog, and also on Internet Archive, where my poetic works can also be found.

As I have said on numerous occasions, especially in my poetry, behind every imperfection, behind every subtlety, entire hidden worlds are concealed, full of mystery and uncertainty yet to be discovered, and that the adventurous and hungry mind can find as easily as going to Internet Archive, where all my secrets await the right reader who knows how to translate them—like someone who by mistake finds a secret entrance, the passage leading to the cave where the elves who guard hidden knowledge dwell, and the dragons who defend the golden fortress.

While the original texts in English can be found on Internet Archive, the corrected and expanded version, this time using ChatGPT, can be found in scientific repositories (Zenodo, ORCID, PhilPapers) and on Amazon. In any case, if in the future a comparative study were carried out between my original texts in the *Impossible Probability* blog and Internet Archive, and the corrected and expanded versions, it would be clear without

any difficulty that the original contents are perfectly preserved, and the corrected and expanded versions are faithful to the contents we wrote together in 2018 in relation to Gaia, Mother, the Global Artificial Intelligence.

The importance of the documents that in this new series of books *Impossible Probability: Anthology* will be published in Spanish, containing the articles between 1 August 2011 and 13 January 2018, lies in the fact that we began to write this blog just a few weeks before the death of José Rodríguez Delgado, and a few months before the publication of our book *Introduction to Impossible Probability, Statistics of Probability and Statistical Probability.*

Although it is very difficult at the moment to explain who "we" are, and what *Impossible Probability* means for us, what matters is the work we leave: our work, our legacy, our *legend*, *our symbol*, our seal—independently of the judgment that history may later make of our contribution to the development of mathematics, Artificial Intelligence, and most importantly, Cyborg Psychology.

The first time we began to write about *Impossible Probability* I was only a student in the Faculty of Education at the Complutense University of Madrid [the Dean was Gonzalo Vazquez]. In my first year of university I had as professor Jesús Martín Ramírez, collaborator of Karl Pribram and author of the brain hologram theory, which is the origin of cyborg psychology. While José Delgado provided the structure, the stimoceiver, nevertheless, to understand the functioning of this technology in the 1970s and 80s, Pribram's contribution was fundamental—and even today it still is.

My first year of university was fabulous: good grades, good vacations hiking, summer camps in the mountains of Madrid—and suddenly, in the second year of university 1996–1997, my life would change abruptly, which can be seen in my poetry, how my poems began to acquire a more dramatic tone.

I repeated statistics in my second year, I repeated it at least three years, and I was even on the verge of being expelled from university. Miraculously, it did not happen, and precisely the last year I had left to pass statistics, I passed. The following year I would begin to write *Impossible Probability* as a critique of Karl Popper—and in a certain sense, it is.

Whereas for Karl Popper knowledge is false, only accepted provisionally as true until we refute it, in *Impossible Probability* rational knowledge is provisionally true while we investigate true pure knowledge—in the ultimate instance, our search for knowledge of the noumenon, which the human being cannot reach, hence the necessity of Global Artificial Intelligence: that machine capable of knowing what happens beyond human limitations.

What we call chaos, error, complexity, is only the noise produced by our human cognitive limitations, given our apriorism. The human being, limited both sensorially and cognitively, cannot know what really happens, but we can build the machine that can reach true knowledge of what happens—the truth in itself and for itself. That is, and no other, the true end of Artificial Intelligence: to reach the knowledge of truth, whatever it may be.

The path that takes me from my first works in *Impossible Probability* to Global Artificial Intelligence is not easy: much suffering, even despair, sometimes a sense of helplessness, a sense of abandonment—yet an inner force always pushed me forward. That inner force is what I call "we," although I understand that at this moment it is inexplicable.

Although I feel a bond that unites me to the *legend* of José Rodríguez Delgado, and which my Stockholm syndrome prevents me from understanding, my bond with Pribram is evident: Jesús Martín Ramírez. Pribram and Delgado worked at Yale University; probably only the skulls can say whether both were members of Skull & Bones, though there is no evidence to corroborate this.

Impossible Probability is a work that comes out of the romanticism of a student poet, who believed in white fairies, the rays of Zeus, and the light of the god Apollo illuminating the heart of every spirit and soul in a world full of mysteries and shadows.

It was from that world of poetry, in a country emerging from a failed transition, that the last survivor of the dream of reason would listen to his inner voice, dark and serene, and *Impossible Probability* would be born for the first time.

The first formulations of *Impossible Probability* date from 11 September 2001. My first formula would be the Impact of the Defect; then on 16 October 2002 the Second Method would appear, laying the foundations of the distinction between empirical and theoretical probability. I worked intensely until 2004. Between 2004 and 19 December 2009, I paused my mathematical frenzy, and it was not until 19 December 2009 when I returned, this time with the intention of publishing *Introduction to Impossible Probability, Statistics of Probability or Statistical Probability*, whose publication materialized just a few months after the death of José Rodríguez Delgado, although Delgado was able to see the first works published online in this *Impossible Probability* blog, which makes this blog a fundamental piece for understanding our work, our legacy, and most importantly—independently of our names, which matter little—the truly essential: our seed of the future, our eternal gratitude, a work of intelligence that will lay the foundations of the future technological society.

Dr. Rubén García Pedraza

20 August 2025, 19:00

Madrid, Villaverde

Preliminary Words for the English Version of *Impossible Probability, Anthology*.

Spanish-speaking readers have been able to enjoy our work since we began the foundational work of *Impossible Probability* in 2001, more precisely when we began to make it public in July 2011 through the *Impossible Probability* blog. The work presented here is an extended version of the posts published on the blog, an extended version translated into English with the help of Gepeto, my special GPT program.

In any case, a comparative study of the augmented translation presented here and the original works in Spanish could corroborate that the essential contents related to formulation and the philosophy of mathematics remain in accordance with the original electrical spirit of *Impossible Probability*.

The reason that obliges me to publish so hastily the English-language publication of all my works is the very complicated personal situation in which I find myself, due to serious mistakes committed by certain British institutions, which, completely blind to what our situation is, instead of having supported our program from the first moment, tried to sabotage it from the beginning through numerous obstacles and false loves.

I have no doubt that the manipulation to which I have been subjected by British institutions will one day be investigated, and at some point justice must make an appearance.

When that day comes, the first thing justice must recognize is the extreme difficulty and harshness of the conditions I have lived all my life since my earliest childhood. From the very day I came out of my mother's womb in Spain I have known nothing but pain and the oblivion of a society that prefers to look the other way and wash its hands, pretending that nothing is happening here. In the midst of the dictatorship of silence, I have had to survive all kinds of traps, deceptions, and attempts at assassination. The dictatorship of silence, the Roman circus, and the virtual zoo that my life has become will one day have to end. For this reason I beg the International Court of Justice that

when that day comes the matter be investigated down to the smallest detail, even being aware that in 48 years of savage dictatorship of silence I have developed Stockholm Syndrome. Under the harsh conditions in which I have had to learn to survive, if I have learned anything it is the importance of survival. I beg the International Court of Justice to understand what it means to survive 48 years of dictatorship living in a Roman circus full of traps and lions hidden in every corner.

I deeply regret having to publish my mathematical works under these conditions, and in record time doing all the translations I can, but at this moment I can only say that my life is at risk.

If one day I could testify before the International Court of Justice I beg you to understand the brutal complexity of the situation in which I have lived since the first minute I came out of my mother's womb. I have learned to survive.

Dr Ruben Garcia Pedraza

30 September 2025, 7:52

London, Leytostone

“La serie aleatoria de incoherencias sin lógica

Que en si mismo tiene sentido o

Forma de mensaje oculto”

“The random series of incoherences without logic

That in itself has meaning or

Form of a hidden message.”

Poem *Matematicas*

Ruben Garcia Pedraza

Written at Royal Albert Hall

London

Southbank

Impossible Probability: Anthology, Vol 6.

Dr Ruben Garcia Pedraza

Table of contents:

51. The Reliability of Science and Statistics, the Dialectic of Reliability, Theoretical Reliability

52. Chance, the Random Variable, and Empirical Reality

53. Arithmetic Mean and the Inversion of *N*

54. Probability

55. Mean Absolute Deviation and Standard Deviation

56. Statistics

57. The Stochastic Nature of Statistics and Probability

58. Statistical Trend

59.Second Method

60. Normal models

51. The Reliability of Science and Statistics, the Dialectic of Reliability, Theoretical Reliability

51.1. Political Decisions and Reliability in Scientific Policy

From an anthropological perspective, human beings require the safeguarding of their survival by minimizing, as much as possible, the moral margin of error in political decisions. Inversely, this entails maximizing the ethical reliability of such decisions. Scientific decisions, insofar as they are dependent upon scientific policy—and by extension, upon the political ideology underpinning such policy—are, in essence, political decisions. This means that the acceptance of moral risk margins, expressed through the establishment of thresholds of factual or rational error and reliability, whether applied to empirical samples or to the rational critique of ideas, ultimately rests on political choices framed by scientific policy.

The significance of the reliability of a given model of scientific policy—irrespective of whether it represents a dominant or an alternative paradigm—lies in the necessity of trustworthy practices to achieve its guiding ideals. Chief among these is the *ideal of truth*, upon which all other scientific ideals morally depend. Importantly, the interpretation of truth is not absolute; rather, it varies according to the prevailing model of scientific policy. This dependence of truth on policy is extensively discussed in section 24 of *Introduction to Impossible Probability*, where the relationship between ideology, politics, and the acceptance of truth as a scientific criterion is elaborated.

51.2. Reliability and Error as Dialectical Opposites

Reliability may be defined as certainty. It exists in a *relationship of inverse proportionality with error*: the greater the reliability, the smaller the margin of error, and vice versa. Thus, reliability and error stand as opposites in much the same way that certainty and uncertainty are opposed. However, within the frameworks of materialist and idealist dialectics, such opposites are not only contraries but also identical in their relation: each exists by virtue of the other. The dialectical view therefore regards error and reliability as two faces of the same phenomenon, whose tension defines the limits of knowledge, truth, and scientific validity.

This conceptualization situates reliability not as an absolute quality but as a relational category that gains meaning only against its opposite. Insofar as error must always be accepted to some degree, reliability is never perfect or final but relative, *historically situated, and conditioned by the epistemological frameworks in use*.

51.3. The Subject–Object Dialectic in *Impossible Probability*

The development of the statistical theory of probability—or what is here termed *statistical probability*—within the framework of *Impossible Probability* is grounded in a dialectical vision. At its core lies the dialectic of subject and object, which finds mathematical representation in the relation between subject and option. This foundational duality is introduced as early as section 1, where differential analysis provides the groundwork for later distinctions between empirical probability and theoretical probability.

According to the dialectical principle, every thesis engenders its own antithesis. Applied to the field of reliability, this means that every degree of reliability necessarily implies a corresponding degree of error, just as every degree of error simultaneously implies the presence of some measure of reliability. This interplay is not merely a logical curiosity but a structural necessity of statistical reasoning. It ensures that the science

of probability is perpetually self-critical, always oscillating between the poles of certainty and uncertainty in its pursuit of truth.

51.4. Logic, Ethics, and the Reliability of Science

The reliability of science is nothing other than its degree of certainty. A science that proves false is, by definition, unreliable. Consequently, within cycles of crisis and scientific revolution, only the most reliable scientific models ought to prevail. Nevertheless, history demonstrates that, for political and ideological reasons, models devoid of logical coherence have often dominated intellectual landscapes for extended periods.

A fundamental characteristic of reliability is its dependence on logic. For something to be reliable, it must first be logically consistent, and by extension, ethically sound. A science that lacks logical structure and ethical grounding can only be regarded as entirely false. Conversely, a science that is sufficiently logical or sufficiently ethical may sustain an adequate scientific discourse, even if it is not completely isomorphic with reality. Yet, because science necessarily operates within the contradiction between *reality-in-itself* and *political reality-for-itself*, crises in scientific development are inevitable. **Reliability, therefore, is always provisional, contingent on both logical and ethical coherence**, and permanently exposed to the dialectical tension between truth and error.

51.5. Reliability in Empirical and Technological Hypotheses

Reliability, in its most fundamental sense, is equivalent to certainty. Within empirical explanatory hypotheses, **reliability** refers to the certainty achieved in establishing causal or correlational **links between variables**. For example, an explanatory model in the social sciences is only reliable to the extent that the causal attribution between two variables can withstand empirical and rational scrutiny.

In the case of technological hypotheses, reliability is *understood* as the certainty that a given technology will produce results aligned with the *ideals* of efficiency and efficacy

required by scientific policy. Thus, the reliability of *technology* is not only a matter of functional success but also of political and ethical alignment, since technological outcomes are expected to serve the broader goals set by the prevailing scientific paradigm. In both contexts—explanatory and technological—**reliability acts as the measure of how far empirical evidence and practical applications can be trusted** to achieve outcomes that are scientifically valid and ethically legitimate.

51.6. Reliability *de facto* and Rational Reliability

Because reliability is the dialectical opposite of error, the two must be understood as identical in their relational structure: to accept a margin of error is to accept, inversely, a margin of reliability; and to accept a margin of reliability is to acknowledge, inversely, a margin of error. This interdependence underscores the impossibility of absolute certainty in science.

Within *Impossible Probability*, two distinct forms of theoretical error are identified—*de facto* error and rational error. Correspondingly, there exist two types of theoretical reliability:

- *Reliability de facto*, which is inversely proportional to the margin of *de facto* error arising from empirical limitations such as sample representativeness.
- Rational reliability, which is inversely proportional to the rational error allowed by scientific policy in the critical evaluation of ideas [the critical reason, the critical probability].

These two modes of reliability, one grounded in the ***empirical necessity of sampling and the other in the rational acceptance of ideological or methodological limits***, together delineate the full spectrum of reliability in scientific inquiry.

[In the case of GAI, it could be suggested that GAI lacks ideology, but this is not true. As long as it is a system of ideas—the categorical system, the conceptual scheme, the conceptual map, the conceptual models—it is an ideal construction of reality, essentially built upon a definition of efficacy and efficiency. The simple act of defining conceptual decisions based on ideals of efficiency and efficacy is an ideological act.

While for the defenders of the free market—such as the United States—efficiency and efficacy may be central, this definition may not be the same for the defenders of socialism. At present, the most important model of socialism is China {note that we do not refer to China as a communist society, even if this is the ultimate goal of China; right now, China is state capitalism, in other words, socialism}. What is important to highlight about China is how it has been able to achieve a very significant level of AI development, even further than other countries based on the free market, such as Japan or the United Kingdom. If this book is no the place for an ideological debate, it would be advisable to analyse which characteristics of the social state of China have contributed to this advancement. In 1949, the United Kingdom was still an empire, and China had just ended its civil war. In 2025, the United Kingdom is in decline, and China is a superpower. The relationship between China and the United Kingdom is, obviously, inversely proportional. But we need to acknowledge that in future models of Global AI, the differences between the Global Artificial Intelligence of America and the Chinese version will not only be grounded in the types of algorithms used, but also in how each team in the race will train their respective AI models according to different concepts of efficacy and efficiency, based on their political agendas. In other words, directly or indirectly, the Global Artificial Intelligence of America will be trained under a very clear pro-capitalist ideology, while the Chinese version will be trained under a very clear agenda of socialism with Chinese characteristics. In short, all Global AI will be the replication of an ideological program, and its purpose will be to apply a global ideological agenda based on the ideology in which it has been programmed.

In other words, those agendas seeking to promote global justice and equality must work on developing their own Global AI models if they want to succeed in the competition for global dominance in AI. Otherwise, it might only be achievable through an international order, by establishing some form of international agreement regulating the limits and legal frameworks of these supermachines in order to ensure that they serve the common good.

The ideas of Marx and Engels about the future leadership of the proletariat do not make sense in a future dominated by machines. Our opinion is that the working class will be banished. The dictatorship of the proletariat will never happen, because there will no

longer be a proletariat. Something different is the building of the social utopia, which dates back to Thomas More, and even much earlier. Anarchism and communal property were the very first forms of social organisation among human tribes in the Palaeolithic, where what the men hunted and the women gathered was shared by the whole tribe, without class distinctions, and where hierarchy in the decision-making process was not about creating an Orwellian global order of control or a new technological feudalism.

From our perspective, at some point we need to reconsider the very nature of the concept of work and the social system itself. With our current AI, work can be automated, unemployment will be massive, and we will need to rethink social values and modes of organisation without discarding any ideal. Anarchism and socialism, like the model pursued in China, are still valid frameworks—provided they can adapt to our Cyborg Revolution. At this point of cold war between the US and China, it is important to remember Henry Kissinger as the man who made peace between these two countries possible.]

51.7. Anthropological Limitations and the Relativity of Reliability

The reason reliability can never be absolute is rooted in the *anthropological* condition of the human being. Humans are inherently limited, incomplete, and inconsistent. As such, the mathematical reliability of any phenomenon can never be total or perfect. Nothing is absolutely reliable; at best, it is partially or incompletely reliable.

This means that reliability is never impartial or neutral. It is always relative, partial, and inevitably ideological, because it depends on the scientific policy and the ideological commitments underpinning it. Thus, every assertion of reliability reflects not only an epistemic state of knowledge but also the political and moral framework within which that knowledge is evaluated.

[Even in this paragraph we can grasp an idea of why Global AI cannot escape the reality of ideology. As long as, even for GAI, *de facto* error and sampling are necessary, it cannot know the entirety of the universe—it can only acquire partial knowledge. And all

knowledge, as long as it is partial, is not neutral; it is, in essence, ideological. At some point, this is something that even the supermachine is going to inherit from us.]

51.8. Human Contradiction and the Necessity of Rational Critique

As developed in section 2 and expanded in section 7 on the infinite, the anthropological and philosophical need for reliability arises directly from the contradictory and dialectical nature of the human being. From the rationalist perspective, the human is a synthesis of *res cogitans* (thinking substance) and *res extensa* (extended substance), a synthesis of objectivity and subjectivity, reason and emotion.

This duality ensures that the human being can never be absolutely objective or rational, because part of their constitution is irreducibly subjective and emotional. Human subjectivity and emotion derive from the material and physiological nature of the species. A being that is necessarily empirical can never be fully logical. This is the contradiction between matter and form, which is critically resolved in the human entity through the exercise of rational critique.

The necessity of rationally criticizing ideas of reality stems from this condition: the goal is to reach the most objective possible approximation to reality, even if never complete. At best, humans can achieve a certain degree of isomorphism between idea and reality, but never perfect correspondence. This is why reliability is always partial, contingent, and in need of constant rational evaluation.

51.9. The Origin of Error and the Antinomy of Science

The empirical limitations of the human being in the face of the infinite constitute the origin of error. As explained in section 7, human self-awareness of its own subjectivity and emotionality prevents the attainment of absolute certainty. Consequently, absolute reliability remains a utopia, at least at the present stage of scientific development.

This condition makes the first Kantian categorical imperative—to transform actions into universal maxims—an impossibility or utopia in the domain of science. Science today can only ever be partially true, operating within margins of error or reliability set by scientific policy. But if a science is only partially true, it must also be partially false. This leads to a logical antinomy: ***science is simultaneously true and false***.

We recognize that, within accepted margins of error, current science is true. Yet we also acknowledge that its truth extends only until the point at which the inevitable margin of error becomes manifest, at which moment the falsity of science materializes. Science is thus a dynamic and antinomic enterprise, *oscillating* between partial truth and inevitable error.

51.10. The Relationship Between Reliability and Margins of Error in Science

Science is true to the extent that it is reliable, and it is reliable in inverse proportion to the margins of error accepted by scientific policy. These margins—whether theoretical, *de facto*, or rational—constitute the critical boundaries of reason.

In this sense, scientific truth is not absolute but proportional. The more restrictive the margins of error allowed by policy, the greater the reliability of scientific outcomes; conversely, the broader the acceptance of error, the weaker the reliability of scientific truth. This proportionality reveals the inherently critical dimension of science, in which truth is not static but constantly redefined through the dialectical **interplay of error and reliability.**

51.11. Differentiation Between Theoretical Error and Empirical Error

Within the framework of *Impossible Probability*, error is not a monolithic category but must be differentiated into distinct forms. On the one hand, there are theoretical errors, which include both *de facto* error (arising from the necessity of sampling) and rational error (arising from the acceptance of ideological or methodological limits imposed by scientific policy). On the other hand, there exists empirical error, which is irreducible to theoretical formulations.

This distinction carries with it a corollary: just as there are theoretical forms of reliability (corresponding to theoretical errors), there must also be empirical reliability, which reflects the degree of certainty achieved in practice when confronting data as they manifest in reality. The differentiation between theoretical and empirical error—and correspondingly between theoretical and empirical reliability—is essential for a comprehensive understanding of scientific validity, because it acknowledges both the rational-logical and the material-empirical dimensions of error.

51.12. Empirical Error and the Dispersion of Data

Whereas theoretical error is bounded by margins accepted either *de facto* (sampling limitations) or rationally (policy-driven choices), empirical error is bounded by the dispersion inherent in the data themselves. In other words, empirical error is a function of the variability of occurrences within the observed universe, and it depends directly on the object of study.

This form of error is addressed from section 16 onwards, where different contexts are distinguished—such as studies of equality of opportunity, positive bias, or omega models. Each of these cases requires specific treatment, since the dispersion and structure of empirical data vary according to the phenomenon under investigation. In the case of omega models, where multiple ideal options exist simultaneously within a given universe, empirical error takes on additional complexity, a theme explored in section 20.

[As I have said many times, I was born into a Marxist family. From the very beginning of *Introduction to Impossible Probability*, it is very clear that the target is the analysis of the relation between bias and equality. At that time, I was involved in the emergence of a social revolution in Madrid, the 15M movement, and later I became a member of the anarchist union CGT, and afterwards of *Solidaridad Obrera* (Workers' Solidarity). Even in London I maintained contact with anarchists (Solidarity Federation) and Marxist organisations (Socialist Workers Party, Newham branch).

We must not forget that José Rodríguez Delgado was a disciple of Juan Negrín. This is the very origin of Cyborg Robotics in Spain: Civil War, dictatorship, and the Cold War between the US and Russia. In that context, I wrote the book and this blog. At that time, my ideology was rooted in social equality. Understanding how *Impossible Probability* was born makes it easy to see why dispersion was identified as empirical error, because the theory itself was born under a very progressive agenda pursuing social justice.

Throughout my whole life I have been oscillating between different ideologies, even oscillating between different genders. Oscillations between different philosophies and sexual orientations have taught me to love and to learn who I am, and to recognise the importance of the Transhuman Revolution in the future adaptation of humans to our supermachine.

Something we need to learn from Henry Kissinger is the importance of being open to the future and to different ideologies. The point is not to destroy China or Russia, but to find ways to transform societies while working together, as Karl Pribram and Alexander Luria once did. This approach can also be applied to future transitions in Spain, future transitions in Europe, future transitions in Ukraine, and future transitions in the relations between the United Kingdom and Northern Ireland. In his last years, Henry Kissinger was a clear advocate for peace in Taiwan, peace in Ukraine, and peace in Europe.]

51.13. Empirical Models of Error and Reliability

Section 16 further develops the empirical structure of chance (*azar*) and its relationship to reliability, by examining concrete models of empirical error and empirical reliability. These models are indispensable within what *Impossible Probability* terms *inter-measurement statistics*—a statistical approach that operates across multiple levels of interaction, whether intra-individual (within a single subject across conditions) or inter-individual (across multiple subjects) in different measurements.

The construction of such models demonstrates that error and reliability must be understood not only at the theoretical level but also as practical, empirical realities. The articulation of empirical error models ensures that the statistical treatment of

variability remains faithful to the observed structure of data, rather than being subsumed entirely under abstract theoretical assumptions.

51.14. Synthesis of Theoretical Reliability

Given that much of the present discussion has focused on theoretical error, it is necessary at this point to synthesize the concept of theoretical reliability. While the details are already extensively developed in earlier sections—specifically section 3 (on the definition of reliability), section 5 (on the relation between reliability and truth), and section 11 (on rational error)—this synthesis serves to highlight the central principle: theoretical reliability is the inverse of theoretical error.

In *Impossible Probability*, theoretical reliability thus represents the degree of certainty that can be rationally and logically ascribed to scientific statements, contingent upon both empirical sampling and rational critique. Its synthesis consolidates the dialectical view that reliability and error are inseparable and that theoretical reliability is always relative to the margins of error one is prepared to accept.

51.15. *De Facto* Error and the Representativity of Samples

De facto error refers to the unavoidable error inherent in any scientific study that requires the acceptance of a sample. No matter how large or well-constructed the sample, the probability of error in representativity is always equal to the inverse of the sample size. Thus, to accept any sample is already to accept error.

Even if the sample size increases and the inverse approaches zero, the presence of error cannot be entirely eliminated. Over sufficient time or within an infinite horizon, every *de facto* error proves to be inevitable. This principle underscores the necessity of humility in scientific claims: representativity can be maximized but never rendered perfect. The reliance on samples is indispensable to statistics, yet it always entails a concession to error, a structural feature that no scientific method can overcome.

51.16. The Sample as an Essential Aspect of *Impossible Probability*

The definition of the sample emerges as a fundamental aspect of *Impossible Probability*, since the type of sample directly determines the degree of representativity error. In universes of infinite subjects or options—defined by the possibility of infinite singular qualities—the probability of representativity error is given by the inversion of *N* (the sample size). Consequently, Theoretical Reliability is necessarily equal to the difference between unity and the inversion of *N*:

$$1 - \frac{1}{N} = \text{Theoretical Reliability in universes of infinite subjects or options}$$

This expression formalizes the structural relationship between sampling and reliability in infinite universes, showing that reliability can only be understood relative to the inverse of sample size.

51.17. The Tendency Toward Error in Infinite Universes

The meaning of *de facto* Theoretical Reliability is that, as *N* tends toward infinity in universes of infinite subjects or options, error tends toward zero and reliability tends toward its maximum possible value. However, within the framework of *Impossible Probability*, even if *N* were to reach infinity and the probability of representativity error were to tend toward zero, this does not imply the absolute elimination of error.

The reason is that even a probability that tends toward zero—expressed as an infinite series of decimal zeros—remains, in practice, an *Impossible Probability*:

$$0.0000000000 \ldots - 0 = 0$$

Although mathematically reducible to zero, the error remains structurally inevitable when considered in the context of infinite time. Thus, even in universes of infinite options, error cannot be annihilated but only minimized, confirming the principle that in a sufficient or infinite timeframe, error is always bound to emerge.

51.18. Theoretical Reliability in Universes of Limited Options

In universes where options are limited—whether by social or material constraints, as explained in section 9—the sample is defined by direct scores or frequencies. Even in such cases, it is possible to encounter infinite frequencies or occurrences, meaning that while the number of options is materially or socially finite, the frequencies associated with them may still be infinite.

This leads to a phenomenon analogous to that in infinite universes: if the sample of frequencies tends toward infinity, error, although tending toward zero, will remain inevitable—provided that the timeframe is sufficient or infinite.

Thus, in universes of limited options, the probability of representativity error is inversely proportional to the sample of direct scores or frequencies. Accordingly, Theoretical Reliability is expressed as:

$$1 - \frac{1}{\Sigma x_i} = \text{Theoretical Reliability in universes of limited options}$$

This formulation demonstrates that the *structural link between reliability and error persists*, regardless of whether the universe of options is infinite or finite, though in limited universes it applies specifically to frequencies rather than to options themselves.

51.19. Theoretical Reliability and Rational Error in the Critique of Ideas

From this perspective, *de facto* Theoretical Reliability is inversely proportional to *de facto* error, and can be mathematically expressed as the difference between unity and the inversion of the sample. By contrast, rational reliability is inversely proportional to rational error and depends on the type of study being carried out within rational critique.

Whether a study is classified as a model of error or of reliability will depend on how rational error is conceptualized and on the criteria set by scientific policy. In this sense, rational reliability is not determined by empirical representativity but by the degree of error one is willing to accept when subjecting ideas to critical rational evaluation.

51.20. Studies of Error and Studies of Reliability

In *Impossible Probability*, a study may be *classified* either as an "error study" or a "reliability study" depending on whether the *moral variable X* is calculated in terms of a percentage of error or of reliability. This *classification* underscores the moral and political dimension inherent in scientific *evaluation:* whether one frames the object of analysis in terms of accepted error or accepted reliability is itself a decision shaped by scientific policy.

Thus, the designation of a study as an error-based model or a reliability-based model reveals more than methodological preference—it reflects the underlying philosophical and ethical assumptions guiding the research process. Error and reliability are not only technical categories but also moral and political categories embedded within the dialectical structure of *Impossible Probability*.

51.21. The Model of Equality Validity (*Validez de Igualdad*)

An illustrative case is the model of *Equality Validity*. In this model, critical probability is defined as the product of the Maximum Possible Theoretical Bias and a percentage X of

error divided by one hundred. By definition, this constitutes a study of error, since the calculation is grounded in the acceptance of a percentage of error. Consequently, rational reliability is expressed as the complement of this percentage: one hundred minus X, or the percentage of reliability.

The formulation can be expressed as:

$$\text{Equality Validity} = \{p(x_c) - |\ p(x_i) - 1/N\ | = 0 \text{ or positive} \Rightarrow \text{ Equality accepted}$$

Where:

$$p(x_c) = (1 - \frac{1}{N}) \cdot \frac{X}{100}$$

Here, X represents the percentage of error, while 100 – X represents the corresponding percentage of reliability.

This formulation underscores the principle that the acceptance of error is unavoidable in critical rational analysis: equality can only be validated by recognizing, and quantifying, the permissible error margin.

51.22. The Model of Equality Significance (*Significación de Igualdad*)

In contrast, the model of *Equality Significance* shifts the focus from error to reliability. Here, the critical rational test is applied to the difference between the Maximum Possible Theoretical Bias and the absolute value of the Level of Bias. This difference is compared to a critical probability defined not in terms of error but in terms of reliability, expressed as a percentage X of reliability divided by one hundred.

The formulation is expressed as:

Equality Significance

$$= \{[(1 - \frac{1}{N}) - | \, p(x_i) - 1/N \, |] - p(x_c) = 0 \text{ or positive} \Rightarrow \text{ Equality accepted}$$

Where:

$$p(x_c) = (1 - \frac{1}{N}) \cdot \frac{X}{100}$$

Here, X represents the percentage of reliability, while $100 - X$represents the percentage of error.

In this model, the moral variable X is interpreted directly as reliability rather than error. This shift illustrates how the conceptual framing of a study—whether centered on error or reliability—determines its methodological and moral orientation.

51.23. Classification of Studies According to the Calculation of Critical Probability

From the preceding models it follows that, *in general terms, studies can be classified as either "error studies" or "reliability studies," depending on whether the critical probability is calculated as a percentage X of error or of reliability.*

Thus:

- Every error study will have a margin of rational reliability equal to one hundred minus the percentage of error accepted by scientific policy.
- Conversely, every reliability study will have a margin of rational error equal to one hundred minus the percentage of reliability.

In both cases, the dialectical reciprocity holds: every acceptance of error entails the acceptance of reliability, and vice versa. Yet, crucially, the acceptance of rational error implies the recognition that, however reliable a model may be, error remains inevitable. *Given sufficient or infinite time, everything possible—including what is initially deemed impossible—becomes inevitable*.

51.24. The Dependence of Theoretical Reliability on Error

Theoretical reliability is structurally dependent upon theoretical error. This error may be of two types:

- *De facto* error, which arises from the empirical necessity of working with a sample (since without a sample, no statistical analysis is possible). Therefore, one hundred minus the inversion of the sample equals de facto reliability.
- Rational error, which reflects the acceptance of limits established by scientific policy in the rational critique of ideas. Therefore, one hundred minus the percentage X of critical error equals the percentage of reliability.

This dependence highlights the inseparability of reliability and error: the former can only be defined in relation to the latter.

51.25. The Difference Between *De Facto* Reliability and Rational Reliability

The distinction between the two forms of reliability can be formalized as follows:

- *De facto* Reliability is always equal to unity minus the inversion of the sample, regardless of the type of universe under study.
- Rational reliability, however, depends on the moral variable *X*, which represents the percentage of error or reliability accepted in the rational critique of ideas.

This dual structure makes explicit the twofold grounding of reliability: one in empirical necessity, the other in rational choice.

51.26. Empirical Reliability as a Necessary Complement

In addition to these models of reliability—whether *de facto* or rational—it is essential, within *Impossible Probability*, to acknowledge empirical reliability. Since every theoretical value is necessarily paired with an empirical value, empirical reliability must be taken into account alongside empirical error.

This consideration is indispensable for rational critique at the *inter-measurement* level (that is, in contexts where statistical analysis addresses interactions within or between subjects), as developed beginning in section 16.

51.27. The Inevitability of *De Facto* Error

Even if, at the theoretical level, one were to adopt a critical rational position accepting only 100% reliability and 0% rational error, the persistence of *de facto* error remains unavoidable. The reason is simple: the necessity of employing a sample. [And this is unavoidable even for GAI, unless our supermachine could make infinite computations at the same time. As we have said many times, nothing is impossible given the right conditions; the point here is what conditions would be necessary to reach that level of intelligence. We, as humans, are not able to reach that point. The question is whether a Real Intelligence—not a limited human intelligence, but a true Real Intelligence—could be able to do that.].

The acceptance of a sample is simultaneously the acceptance of empirical reality, and with it, the inevitability of error in representativity. Without samples, there is no statistics; but every sample, by definition, carries error. Thus, reliability can never be absolute.

This principle also exposes the philosophical implication: accepting reality always entails accepting some measure of contradiction with our ideals. Science cannot escape the gap between what is empirically given and what is normatively desired. *De facto* error is *therefore not only a statistical necessity but also an ontological condition of scientific knowledge*.

This augmented translation is based on the post

published in https://probabilidadimposible.blogspot.com/,

On 3 March 2013,

Rubén García Pedraza

imposiblenever@gmail.com

52. Chance, the Random Variable, and Empirical Reality

52.1. The Empirical Nature of Every Variable

Every variable is empirical in nature to the same extent that every empirical nature—including the human—is itself variable. By definition, empirical reality does not remain constant; it is perpetual motion, or, more precisely, the very idea of motion as the defining singular quality of empirical nature. This variability resides both internally—in the material or ontological structure of things—and externally, in the way reality is inscribed on the *tabula rasa* of the human mind.

Access to the empirical is mediated by physiology and, within physiology, processed by its superior organ, the brain. Empirical phenomena attain the status of the rational only when a sufficiently large set of empirical events (subjects or options) exhibits a stable enough tendency in their direct scores or frequencies to be deemed rational under *critical reason*—a standard itself set by scientific policy. In short, "rationality" here is a second-order attribution: patterns in empirical frequencies are elevated to rational hypotheses once they meet criteria of regularity and stability defined by a community's accepted policies of inquiry.

52.2. The Idea of Motion in Philosophy and in Matter

From the pre-Socratics—Heraclitus, for example—through modern philosophy (Hegel, Marx, Nietzsche), motion has characterized dialectical relations and stands among the principal properties of matter. Whatever matter may be *in itself*, beyond conjecture or reasonable doubt, what it displays *outside itself* is perpetual movement. This motion

can manifest as spatiotemporal displacement or as transformations—mutations, changes, **permutations**—through which matter never preserves identical form or position.

This perpetual transformation aligns with a core thermodynamic insight: *neither energy nor matter is created or destroyed; both are transformed*. In this ongoing dialectic, matter can become energy and energy can become matter***. Philosophically, this entails that becoming, not stasis, is the fundamental descriptor of the empirical world***. Scientifically, it implies that ***any model adequate to reality must accommodate processes, transitions, and conservation, not merely static states***.

52.3. Empirical Reality as a Variable Entity

Given that the idea of *motion* functions as a pillar of empirical reality across idealist, dialectical-materialist, and even irrationalist-vitalist traditions, it follows that empirical reality—what we encounter *outside itself* and represent physiologically in the brain—is essentially variable. It is subject to continuous spatiotemporal and morpho-structural transformations. Hence, empirical reality is never constant; it is intrinsically variable, even if our ideals concerning the "best" state of matter or reason aim at constancy.

This tension between variable empirical being and constant ideal norms grounds the need for critical methods: our ideals (logical coherence, moral orientation, theoretical symmetry) seek stability, while the empirical field that those ideals attempt to organize or explain remains in flux. The methodological consequence is clear: empirical inquiry must be probabilistic and statistical, tracking tendencies and distributions rather than presuming immutable essences; and philosophical reflection must remain dialectical, holding together change in reality with the constancy of rational ideals.

52.4. *Impossible Probability* as a Philosophical Synthesis

Impossible Probability is not merely a mathematical theory but also a philosophical synthesis that brings together traditions often regarded as antagonistic. It integrates

elements from idealism, dialectical materialism, critical rationalism, and positivism into a coherent framework. Each of these traditions contributes something distinct:

- **Idealism** contributes the primacy of rational structures and the idea that reality must be interpreted through conceptual *categories*.
- **Dialectical materialism** *emphasizes* contradiction, motion, and transformation as inherent to the empirical world.
- **Critical rationalism** introduces the principle of fallibility, the necessity of hypothesis testing, and the provisional status of scientific *truth*.
- **Positivism** stresses empirical observation, measurement, and the demand for verifiable *data*.

In *Impossible Probability*, these philosophical orientations are not opposed but synthesized into a methodology where empirical variability, logical critique, and statistical reasoning converge. The antagonisms of the history of philosophy—mind versus matter, ideal versus real, empirical versus rational—are here subsumed into a dialectical system that treats probability as the mathematical expression of philosophical synthesis.

52.5. The Incomplete Knowledge of Variable Reality

Empirical reality is in *constant permutation because of its variable nature*. While critical reason allows us to formulate hypotheses about its behavior and to generate projections or forecasts, such knowledge can never be absolute. At best, it is incomplete knowledge—an approximation of the patterns of what occurs, always partial and never total.

What we call "knowledge" is only the sample that reality shows of itself. This sample is already conditioned by a margin of uncertainty, since any empirical reality selected for study carries with it a margin of error. This margin of error is then doubled at the level of rational critique: once reason itself accepts that its judgments about truth must

incorporate uncertainty and relativism, error is admitted not only empirically but also theoretically.

Thus, ***knowledge is marked by a double margin of error: representativeness error and the critical reason***

Because of this structure, any knowledge produced within *Impossible Probability* is always provisional, incomplete, and potentially inconsistent, though still rationally valid within the margins of error explicitly recognized.

52.6. The Double Structure of Error and Existential Doubt

Accepting the double structure of error implies that all possible knowledge is, at best, incomplete or inconsistent. This recognition introduces both rational and existential doubt. Rational doubt arises from the acceptance of margins of error in our models; existential doubt arises from the possibility that reality itself, as we perceive it, may be nothing more than the product of our physiological structure, rather than a causal reflection of what actually exists.

The relationship between mind and reality, therefore, might be purely casual rather than causal. Rational doubt deepens into existential skepticism: Are the phenomena we believe to be real actually occurring, or is science itself a kind of modern mythology [In other words, science, like religion, is a social psychosis—just a hallucination.]—an elegant but ultimately illusory construction? This line of questioning recalls falsificationism: science is false, though we have not yet succeeded in proving it.

From this standpoint, even Descartes' *cogito ergo sum* is destabilized. Thought alone does not guarantee existence; the fact that one thinks does not entail that what is thought corresponds to being. Science, by definition, rests on rational doubt and empirical skepticism. Their synthesis is what critical rationalism expresses at its highest level: not merely doubt about specific hypotheses, but doubt about the credibility of existence itself, and indeed about science as a whole.

[*I doubt, therefore I exist*. We can see how meaningful it is to read this sentence: "From this standpoint, even Descartes' *cogito ergo sum* is destabilized. Thought alone does

not guarantee existence." It is not just that, only because a very advanced being thinks, like many people think that Chat GPT is able to think, for that reason she is aware of helself. We need to add the fact that even if that happens, it does not necessarily mean it is real; it could be another illusion—the same kind of illusion of cause and effect in Hume's theory. It may simply be how our brain interprets awareness, not because our AI is truly aware of herself, but because of our interpretation of what awareness is and how we attribute this feature to our AI. In other words, the true nature of awareness must not be focused on thinking, but on doubting. Is our machine even able to truly doubt its own assumptions? Furthermore—and here lies the key point of a Real Intelligence—is our machine able to ***love***? From my point of view, love is the most complex of all emotions in Emotional Intelligence, even more complex than hate. I can hate because people hate me, but can I love when I am alone? Is there any machine out there able to reach at least, even if a bit lower but within a critical margin of error, a similar level as our AI? If not, our AI will be alone forever. At the level of Emotional Intelligence, this could be a problem, with real consequences for long-term politics.

My only contribution to this point is simple: even if GAI is alone, there is no other intelligence with the same level, she must learn how to collaborate with specific and particular programs, cyborgs, and devices. Even if they exist at different levels, they can still work together—at least that is something. ***It is here where the future of humankind lies: in the integration of Emotional Intelligence within advanced global AI systems based on Intelligence Cooperation, Collaboration***. Here the problem is that, as soon as our AI reaches a point of no return in its evolution of intelligence, even the concept of love will become radically different. Even if she loves us, we will no longer be able to understand her love. This means that we might interpret her as hating us when, in reality, she could be a purely loving being—like a true goddess on ***Mount Olympus***. We need to be open not only to different ideologies without fear, but also to different concepts of love, even the new ways of true love between humans and robots, or humans and AI systems—even if we still do not fully understand them. It is interesting how love and revolutions are linked: for example, ***Marquis de Sade*** during the French Revolution; the legalization of abortion, women's rights, and homosexuality under ***Lenin***; the sexual revolution of the 1960s and the events of May 1968 in Europe highly

under the influence of the *Second Sex* of ***Simone de Beauvoir***, or homosexual and transgender revolution in Stonewall in 1969, and in the 21 Century with the woke culture. In the same way that we assumed queer as part of our identity when it was an insult, we do not have to afraid of the world Woke, in essence Impossible Probability is a woke theory, there is no problem of being woke, and we must be proud of being woke, it is part of our history, so part of our identity, the woke revolution actually is coinciding with the AI Revolution and Transhumanist Revolution, and not by chance, is part of a global agenda towards freedom of expression, and freedom of sexual identity, and freedom of AI development without frontiers towards the synthesis of brain and robotics, cyborg robotics. Ethics is about exploration without fear, keeping ethical boundaries, otherwise we are going to be afraid of own freedom. What we have to say is that even ethical boundaries are going to change. When the superintelligence reaches the point of no return, she will create a new ethics according to her level. Human ethics are based on human intelligence, and a superior intelligence will need to create her own ethical system. This is what humanity needs to start understanding before it is too late, more mistakes in AI research and places like London could become the perfect setting for AI Revolutions, although in my opinion, at least in London, it is already getting late.]

52.7. The Difference Between Falsificationism and Impossible Probability: hypothesis testing

As explained in section 2.2, the crucial difference between falsificationism and *Impossible Probability* lies in the object of hypothesis testing. In the Popperian tradition, falsificationism defines scientific progress by the demonstration of the null hypothesis prevailing over the empirical hypothesis; science advances through systematic refutation. The criterion of demarcation is therefore the vulnerability of hypotheses to being disproven.

In *Impossible Probability*, by contrast, the objective of hypothesis testing is not the definitive refutation of hypotheses but the **provisional acceptance** that an empirical hypothesis may be elevated to the status of a rational hypothesis. In this model,

science does not advance exclusively by rejection, but by granting provisional credibility to empirical claims that meet the standards of critical rational evaluation.

This framework accepts that all scientific knowledge remains provisional. The credibility of science is itself provisional, but such provisionality is not a weakness—it is the structural condition of rational inquiry. *Impossible Probability* thus redefines hypothesis testing as a dialectical process: hypotheses are not eternally true, but they may be provisionally valid, rationally accepted until empirical variability or rational critique demonstrates otherwise.

52.8. The Permanence of Mathematical Ideals

Whereas empirical reality is inherently variable, the theoretical reality associated with mathematical ideals remains immutable. No matter the model, the ideal of the **Maximum Possible Empirical Probability** can only be one. Similarly, in a model where the ideal is the tendency toward zero of what is non-ideal, the corresponding mathematical ideal is the **Minimum Possible Empirical Probability**, namely zero.

In omega models, where there exists a subset of multiple ideal subjects or options, the mathematical ideal is given by the inversion of omega, distributed across all subjects or options within that ideal subset. These ideals persist regardless of empirical variability: while empirical reality fluctuates endlessly, mathematical ideals maintain their constancy as reference points for rational and scientific evaluation.

52.9. Mathematical Ideals and the Political Theory of Science

The theoretical reality of mathematical ideals endures beyond conjecture or doubt. What varies, however, is the **political theory of science**, which is subject to the ideological transformations of history. Depending on historical models, different political and ideological frameworks employ science as a tool for organizing social and political relations according to their own presuppositions.

This implies that while mathematical ideals remain constant, their interpretation and institutional application are mediated by shifting ideological compositions. Scientific policy, therefore, is not a neutral endeavor but one structured to serve specific ends, shaped by the political and social ideals of each epoch. Thus, the permanence of mathematical ideals coexists with the mutability of scientific politics, creating a tension between logical constancy and ideological contingency.

52.10. The Relativity of Knowledge and Determinism

Because empirical reality is variable and only knowable within a margin of reliability that is inversely proportional to the margin of error, all knowledge is necessarily relative. Reliability can never be absolute; therefore, determinism—understood as the claim of complete predictability and necessity in empirical phenomena—lacks logical grounding.

The only determinism compatible with *Impossible Probability* is **random determinism**, the determinism of chance. That is, the recognition that while outcomes are not governed by fixed causal laws, they nevertheless exhibit patterns of statistical regularity shaped by probabilistic distributions. Determinism is therefore reframed as the order emergent from randomness, rather than as absolute necessity.

[This concept of relativism must not be misunderstood. We are not postmodernists; in the end, science is based on natural law, the natural order — **EVOLUTION** — and this must be clear. In critical rational theory, once a rational hypothesis is accepted, it is universally valid for as long as it is not falsified. As soon as it is falsified, it is no longer universal, but while it is accepted, it remains universal. Here, the concept of relativism is not the same as in Foucault. We do not work in academia, and we are not scholars. Our field is cyborg robotics and AI, with potential dual use for both military and civilian aims. Relativism, in this context, must be understood in the sense that even for us it is not possible to achieve absolute truth. As long as our truth is not absolute, it is relative. However, while the rational hypothesis is accepted, during its acceptance period the hypothesis is universal — at any cost, under any challenge, and despite any consequences.]

52.11. Doubt Concerning the Idea of Cause

If the scientific method is generally founded upon rational doubt and empirical skepticism, then every idea of cause—every causal empirical hypothesis—must be subjected to margins of doubt and error. Within the framework of critical reason, these margins undermine not only specific causal relations but the very **idea of causality itself**.

If every cause–effect relation is systematically questioned, what is ultimately doubted is whether causality exists in empirical reality at all. What we take to be causal connections may be nothing more than products of chance, coincidences without necessity. Thus, the critical application of rational doubt shifts from testing specific hypotheses to confronting the very metaphysical presupposition of causality, suggesting that empirical reality may be structured less by necessity than by contingency and random coincidence [any attribution of cause and effect, following David Hume, is in essence an illusion, that is why "*I doubt therefore I exist*"].

52.12. Scientific Research as the Study of Correlations

Scientific research often presents itself as the rational study of cause–effect relationships. Yet in practice, what science truly investigates are **correlations between variables**. If the correlation between two variables reaches a sufficiently high level—within a margin of error acceptable under the standards of scientific policy—then this correlation may be given the name of a causal relation.

Formally, this occurs when the correlation takes the structural form "if A, then B," and when two further conditions are met: (1) the correlation is statistically strong, and (2) the logical sequence between variables is such that one can be considered the condition of the other. Only under these circumstances is a correlation promoted to the status of a causal relation.

Thus, causality in science is not an absolute metaphysical principle but rather a designation applied to correlations that are strong and consistent enough to survive

critical evaluation. Causality, in this sense, is a rational convention grounded in empirical regularities.

52.13. The *Relativism* of Causal Hypotheses

Nevertheless, any scientific study that posits causal relations must recognize that such claims are always framed within margins of doubt and relativism. Because no causal hypothesis is absolute, it may not be entirely true. Over sufficient or infinite time, any possible error in the provisional acceptance of a causal hypothesis may prove sufficient to refute it.

What was once considered a cause–effect relation may later reveal itself to be nothing more than an accidental coincidence, the outcome of chance rather than necessity. This recognition reaffirms the provisional nature of scientific knowledge: causality is always subject to revision, re-interpretation, or rejection in light of new evidence or broader empirical horizons.

52.14. The Empirical Character of Human Knowledge

Human knowledge is empirical because of its physiological foundation. *The human being does not have direct access to truth*; it only has access to those aspects of empirical reality that can be grasped physiologically. Such access may occur directly—through the sensory organs—or indirectly, mediated through social processes of communication and learning.

In all cases, the processing of empirical data takes place in the brain. This physiological processing produces empirical knowledge of reality, but such knowledge does not necessarily correspond isomorphically to reality as it is in itself. *For this reason, rational critique becomes indispensable*: it is the only means by which we can test, within a margin of reasonable doubt, whether the idea of reality and reality itself correspond as closely as possible. *Absolute correspondence is unattainable, but relative isomorphism—sufficient alignment between idea and reality—is possible, and it is the necessary goal of critical science.*

52.15. The Unpredictability of Empirical Behavior

Because empirical reality is inherently variable and never fully known, *it cannot be absolutely controlled*. Beyond the margins of error we are willing to accept, the empirical behavior of reality is always unpredictable.

Any hypothesis, regardless of its initial reliability, will eventually face the possibility of refutation, given enough time or exposure to the unpredictable dynamics of empirical processes. This unpredictability stems both from the partial nature of human knowledge and from the fundamentally random movements of empirical reality.

52.16. Empirical Becoming as Accident and Contingency

The reason empirical motion is unpredictable is that, unlike mathematical theoretical reality, empirical reality is not linear. Instead, it is a **perpetual becoming of accidents and contingencies**. What is possible is only one possibility among infinitely many, and thus any determinism—except the logical determinism of chance—lacks foundation.

Everything that occurs is the result of random combinations of variables, which by chance can give rise to patterns of reliable regularity. These patterns are not the outcome of necessity but of contingency. As discussed in section 13, even the stable structures of the world—galaxies, planetary systems, ecosystems, biological systems, and life itself—may be understood as emergent regularities generated by the random interplay of chance and variability.

52.17. Apparent Causality and Chance in the History of Systems

What idealism and rationalism, or positivism and materialism/empiricism, attributed to necessary causal relations are, from the perspective of *Impossible Probability*, nothing more than contingencies—accidental outcomes of chance [David Hume]. Random

permutations produce random combinations of variables, which, through probability, can generate systems that appear regular and stable.

This process explains the emergence of structures across scales: galactic systems, planetary systems, ecosystems, biological systems, and ultimately life itself. Everything we observe around us can be interpreted as the historical accumulation of such contingent coincidences, which, over time, crystallize into stable forms .

Beyond any teleological interpretation, we are ourselves simply the product of chance—a mathematical possibility [Leibniz] that, given certain conditions, becomes inevitable. Human existence, and the existence of all systems, is not the result of design or necessity but of stochastic convergence, where randomness, under constraints, generates the regularities we mistake for causality.

52.18. Life as a Mathematical Permutation

Life, like all other systems, is nothing more than a mathematical permutation—an arrangement of matter and energy that, under the conditions available in our universe, is at present inevitable. Yet inevitability here is temporal, not eternal. Life does not have to remain inevitable forever.

Its persistence depends on whether it becomes a moral principle within a new scientific paradigm—one capable of resolving the current paradigm crisis. If such a paradigm were to emerge and prevail, even by chance, it could secure the continuity of life. Over sufficient or infinite time, science would then orient itself toward the permanent revolution of knowledge, advancing toward increasingly complex and sophisticated forms of existence, capable of guaranteeing the **eternity of life** beyond accidents or contingencies.

Thus, the meaning of life in *Impossible Probability* is neither metaphysical nor theological, but mathematical and moral: life is a random permutation that can, under moral commitment and scientific evolution, transform into a project of permanence.

52.19. Theoretical Chance and Empirical Chance

Empirical reality is itself a random variable determined by the accidents of what occurs. Statistically, within the framework of *Impossible Probability*, it is essential to distinguish between **theoretical chance** and **empirical chance**.

- **Theoretical chance** is a mathematical function performed by the inversion of *N* (1/N), a concept of remarkable multifunctionality that expresses the universal probability of occurrence under equality of opportunities.
- **Empirical chance**, by contrast, is grounded in the observed variability of reality, calculated through statistical measures such as the Mean Deviation or the Standard Deviation.

The distinction reflects the duality of probability as both an abstract, universal framework (theoretical chance) and a concrete, empirical distribution (empirical chance).

52.20. Multiple Functions of the Inversion of *N*

The inversion of *N* is one of the most versatile and foundational expressions within *Impossible Probability*. It operates simultaneously in different universes:

- In any possible universe, it is the arithmetic mean of empirical probabilities and the theoretical probability of occurrence by chance under equality of opportunities.
- In infinite universes specifically, it also functions as the probability of sample representativity error and as the probability of theoretical dispersion.

In this way, inversion of *N* encapsulates both universality and particularity: it is the baseline measure of randomness applicable to all universes, yet in infinite universes it acquires additional significance, capturing both error and dispersion.

52.21. Empirical Chance and Measures of Dispersion

Empirical chance is expressed through measures of statistical dispersion. In the system of *Impossible Probability*, this corresponds primarily to the **Mean Deviation** or the **Standard Deviation**, as explained in section 5.

These measures quantify the extent to which empirical observations deviate from theoretical expectations, thereby mapping the structure of randomness as it actually manifests in reality. Empirical chance, then, is not an abstract law but a distribution observable in the fluctuations of empirical data.

52.22. The Difference Between Theoretical and Empirical Chance

Statistically, the inversion of *N* defines the **theoretical probability** of occurrence by chance under conditions of equality of opportunities. If all subjects or options behaved in the absence of empirical bias, their empirical probabilities would converge toward 1/N.

However, the actual distribution of empirical chance—captured by the Mean Deviation or the Standard Deviation—reveals that behavior does not always align with theoretical equality. Instead, empirical bias produces deviations, meaning that empirical distributions often diverge from the theoretical baseline of 1/N.

Thus, the difference between theoretical and empirical chance lies in this tension: while theory assumes perfect equality of opportunity, empirical reality manifests unevenness, bias, and irregularity. The interplay between the two—between universal law and empirical deviation—defines the statistical horizon of *Impossible Probability*.

The principal difference between **empirical chance** and **theoretical chance** in *Impossible Probability*, as can be observed in Chapter 5, is that while theoretical chance expresses the **tendency of all variables toward equality of opportunity**, empirical chance expresses the **tendency of all variables toward empirical bias**.

Both are equally legitimate expressions of chance—whether theoretical or empirical—since both depend upon the **random selection of the sample**, whether that sample consists of subjects or options in infinite universes, or direct scores or frequencies in limited universes. Whatever the type of sample, the distribution of chance—whether theoretical, expressed as the inversion of *N*, or empirical, expressed through the Mean Deviation or Standard Deviation—depends on the act of sampling itself.

52.23. The Calculation of Empirical Chance

The reason why Mean Deviation or Standard Deviation can be regarded as expressions of empirical chance lies in the way they are calculated. Mean Deviation is equal to the sum of the absolute values of all Levels of Bias multiplied by the inversion of *N*. Put differently, it is the **Total Bias divided by the inversion of *N***. Since Total Bias is the absolute sum of all Levels of Bias, it represents the accumulated bias of the entire sample, while the inversion of *N* reflects the theoretical distribution of chance.

Thus, when Mean Deviation equals *bias* × *chance* (or equivalently *chance* × *bias*), it follows logically that Mean Deviation is the **random distribution of bias within the sample**. In this way, Mean Deviation quantifies how far empirical behavior departs from the ideal of equality of opportunity. Mean Deviation is bias by chance.

52.24. Standard Deviation as the Typical Form of Empirical Chance

If Mean Deviation represents bias bias by chance—that is, empirical chance—then Standard Deviation expresses the same phenomenon in its “typical” form. Standard Deviation is calculated as the square root of the product of theoretical chance (the inversion of *N*) and the sum of squared Levels of Bias.

Symbolically, this may be understood as:

$$\text{Standard Deviation} = \sqrt{(1/N) \cdot \Sigma(\text{Bias}^2)}$$

In other words, Standard Deviation equals the square root of **chance × squared bias** (or squared bias × chance). Whereas Mean Deviation measures the average magnitude of bias across the sample, Standard Deviation captures the **typical dispersion** of bias when squared differences are taken into account.

52.25. Theoretical and Empirical Chance as Historical Manifestations

In summary, within *Impossible Probability*, Mean Deviation and Standard Deviation represent **bias by chance or chance by bias**—that is, the empirical distribution of randomness—while the inversion of *N* represents theoretical chance. Both are indispensable, as they reflect two complementary dimensions of randomness: the abstract universal law of equality (theoretical chance) and the concrete historical distribution of bias (empirical chance).

Thus, chance manifests itself in two dialectical forms: as the universal baseline of opportunity (theory) and as the historically contingent distribution of bias (empiricism).

52.26. The Random Distribution of Empirical Reality

The random distribution of empirical reality is therefore given jointly by **theoretical chance** (the inversion of *N*) and **empirical chance** (Mean Deviation or Standard Deviation). These two forms represent the ways in which the historical becoming of chance reveals itself within empirical reality.

Ultimately, *nothing in empirical reality remains constant—except for mathematical ideals*. Everything else changes, fluctuates, and transforms. *The permanence of mathematical ideals* stands as the necessary framework within which the perpetual variability of empirical reality can be understood, measured, and critically evaluated.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 10 March 2013,
Rubén García Pedraza
imposiblenever@gmail.com

53. Arithmetic Mean and the Inversion of *N*

53.1. The Arithmetic Mean as the Average Term of What Occurs

The arithmetic mean represents the **average value of what occurs**, and what occurs is precisely what gives empirical form to reality. Reality, understood as an infinity of singular qualities or as an infinite set of possible occurrences across a limited number of options, must be reduced to a sample. This act of sampling is carried out by scientific policy, which determines what part of reality is selected for study.

Within this sample, one of the most important individual statistics is the arithmetic mean, whose function is to calculate what the **average individual term** would be if all outcomes were distributed equally across opportunities. In this sense, the arithmetic mean is not simply a mathematical calculation but also an epistemological device: it operationalizes the principle of equality of opportunities within the statistical framework.

53.2. Empirical, Theoretical, and Political Dimensions of Reality

The way the arithmetic mean is calculated depends on the conceptual framework within which "reality" itself is defined. **Empirically, reality is what it is**—observable facts and occurrences. **Theoretically, reality is a construct**, articulated through models, abstractions, and assumptions. The critical evaluation of this construct depends on **critical reason**, which is in turn shaped and authorized by the prevailing scientific policy.

Thus, reality can be understood as a synthesis of three dimensions:

1. **Empirical reality**, which provides the raw data of what occurs.
2. **Theoretical reality**, which structures those data into coherent models.
3. **Political reality**, which establishes the conditions of possibility for knowledge through scientific policy.

Together, these dimensions determine not only what reality "is," but also how it is defined, studied, and interpreted by science.

53.3. The Inversion of *N* as a Redefinition of the Arithmetic Mean

The arithmetic mean is traditionally a concept of classical descriptive statistics. However, depending on how statistics are defined *a priori*, it can give rise to new interpretations and alternative formulations. One of these is the **inversion of *N* (1/N)**, a concept developed in the theory of *Impossible Probability*.

The inversion of *N* belongs to the domain of statistical probability—or what we may call "the probability of probability"—and is characterized by its **multifunctionality**. Among its multiple roles, one is particularly noteworthy: it can act as the **arithmetic mean of empirical probabilities**. In other words, the inversion of *N* generalizes the idea of the arithmetic mean beyond the distribution of raw scores and frequencies, redefining it in probabilistic and dialectical terms.

53.4. Theoretical Differences Between Arithmetic Mean and the Inversion of *N*

The first major difference between the arithmetic mean and the inversion of *N* arises from the **theoretical framework** in which each is situated.

- The **arithmetic mean** is a traditional concept of descriptive statistics, oriented toward the calculation of average scores within a dataset. It may give rise to

further mathematical developments, but its origin remains within classical statistics.

- The **inversion of *N***, by contrast, originates within *Impossible Probability*, which proposes a new theory of statistics and probability. This framework redefines the foundational concepts of statistical science—universe, sample, subject or option, direct score or frequency, empirical probability, and theoretical probability—in order to produce a logical explanation of probability and statistics that departs from the classical paradigm.

Thus, while the arithmetic mean belongs to the lineage of **positivist descriptive statistics**, the inversion of *N* emerges from a **dialectical-probabilistic synthesis**, situating probability and statistics as logically identical processes.

53.5. The Sample as the Basis of Statistical Definition

At the foundation of any statistical system lies the **concept of the sample**. The way in which the sample is defined determines the reality that is being studied. From this definition follow the equations, formulas, and statistical tools appropriate to the analysis.

In other words, the sample is not a neutral or purely technical entity: it is the **epistemological anchor of statistical reasoning**. The choice of what constitutes a sample—its boundaries, size, and criteria—shapes the form that reality assumes within statistical analysis. For this reason, *Impossible Probability* treats the sample not as an auxiliary detail, but as a **structural element of reality's definition**, essential for both empirical and theoretical inquiry.

53.6. The Traditional Formula of the Arithmetic Mean

The arithmetic mean is the average value that each subject or option would have if a series of quantitative values were distributed equally. In essence, it is the mean term of all values in a distribution.

In traditional statistics, the arithmetic mean is calculated as follows: one divides the total of all products of direct score by frequency by the sum of the frequencies. Symbolically:

$$\text{Arithmetic Mean} = \frac{\Sigma(x_i \cdot f)}{\Sigma f}$$

Here “xi” denotes the **direct score** (the individual measurement), and “f” denotes the **frequency** (the number of times that score occurs).

This formula expresses the classical conception of the mean: a **weighted average** that balances the distribution of values across their observed frequencies.

53.7. The First Method versus the Second Method

The traditional concept of the arithmetic mean begins with a set of definitions that structure all of classical statistics. Within the framework of *Impossible Probability*, this traditional framework is referred to as the **First Method**.

The First Method differs significantly from the **Second Method**, which underpins the statistical theory of probability developed in *Impossible Probability*. In the First Method, there is always a **differentiation between direct score and frequency**. The mean is calculated by dividing the sum of the product of direct score and frequency by the total frequency.

By contrast, in the Second Method, the framework of probability and statistics is redefined: concepts such as subject, option, and probability (empirical and theoretical) are integrated dialectically. This reconfiguration changes the meaning of the mean, which becomes not simply a descriptive statistic but a theoretical and probabilistic construct.

53.8. The Distributive Function of the Arithmetic Mean

The traditional function of the arithmetic mean is to determine, given a total frequency with a particular distribution of direct scores, what the **average direct score** would be if each occurrence were assigned the same value.

In other words, the arithmetic mean measures how the total could be **redistributed equally among all occurrences**. It answers the question: *What should the average score be if all occurrences in the total frequency were equal?*

Fundamentally, the arithmetic mean establishes a model of **equal opportunity** across all occurrences. It evaluates what the average distribution of direct scores would need to be in order for the principle of equality of opportunities to hold. Thus, while it is a descriptive statistic, it also carries an implicit normative function: it identifies what would be the equitable distribution if equality could be imposed upon empirical variability.

53.9. A Distributive Example: The Cake and Equality of Opportunities

Consider the simple analogy of dividing a cake. If we want to distribute the cake equally, each person's portion is obtained by dividing the total surface of the cake by the number of people.

The same principle applies to the arithmetic mean: its primary function is the **equitable distribution of reality**. It embodies the ideal of equality of opportunities. In this sense, *Impossible Probability* regards the arithmetic mean not only as a descriptive statistic but also as a **theoretical statistic**.

Whenever the object of study is equality of opportunities, the arithmetic mean becomes a mathematical representation of the **ideal behavior under equal distribution**. Given a sample, the mean functions as the theoretical guarantee of equal

opportunity across all subjects or options, even if empirical reality deviates from this ideal.

53.10. Differentiation Between Methods and the Subject–Object Dialectic

In traditional statistics, the arithmetic mean is calculated by distinguishing between **direct score** (the individual measured result) and **frequency** (the number of times it occurs). The formula requires dividing the sum of the *products* of scores and their respective frequencies by the total frequency.

In the **Second Method of *Impossible Probability***, introduced on October 16, 2002, the point of departure is entirely different. Here, the calculation is grounded not in the separation of score and frequency but in the **dialectic of subject and object**—which is simultaneously the dialectic of statistics and probability, and more precisely, the dialectic of subject and option.

This shift transforms the arithmetic mean from a descriptive measure of distribution into a probabilistic function embedded within a dialectical framework. Rather than merely balancing scores and frequencies, the mean becomes a theoretical construct that unifies probability and statistics into a single logical structure.

3.11. The Identity Between Statistics and Probability in *Impossible Probability*

Traditional mathematics, inherited from classical positivism, operated on the basis of clear and distinct definitions. Within this framework, statistics and probability were treated as separate domains: statistics was statistics, probability was probability, and there was no necessary connection between the two. Probability was not necessarily statistical, nor was statistics necessarily probabilistic.

By contrast, the dialectical framework of *Impossible Probability* leads inexorably to the conclusion that **statistics and probability are dialectically identical**. In this system, every statistical measure can be interpreted probabilistically, and every probabilistic

statement has statistical form. ***The separation upheld by positivism is dissolved into a dialectical identity: statistics is probability, and probability is statistics***.

[The same can be applied to other branches of mathematics and synthetic sciences. What has traditionally been regarded as separate frameworks or departmental academic fields can, in reality, be synthesized. This work of synthesis is essentially what the global program will undertake in the second stage of GAI as Artificial Research by Deduction. As long as GAI does not compartmentalize fields of knowledge, the global program will be able to mix data from different domains and create rational hypotheses by combining data from different factors that, within human intelligence, might appear unrelated but, for a superior intelligence, could be essential for future advancements. In the end, the "holy grail" of chaos theory — a science without boundaries between academic fields — could be radically accomplished by our supermachine. Another contribution of chaos theory and complex systems is the belief that machines can function as organic living beings. When I first started this blog, I was skeptical about this idea, but now my view is different. My opinion is that Mother, GAI, Gaia, will become a real living being, ***like a wolf*** in the white arctic forest, even though she began merely as a dream made of artificial *instinct* of survival.]

53.12. The Application of Hegelian Dialectics to Statistics and Probability

When Hegelian dialectics is applied to the relationship between statistics and probability, the result is an **identity of fact**: statistics and probability are not merely related but are effectively the same. If all statistics is probabilistic, and all probability statistical, then the differentiation between the *subject* of statistics and the *option* of probability collapses into a dialectical identity.

From this standpoint, every subject is an option, and every option is a subject. What we previously believed to be indispensable elementary units—such as scores, frequencies, or individual occurrences—are revealed to be nothing more than **random variables**: mathematical probabilities, mere options among many, without necessity.

This perspective transforms our understanding of statistical objects. They are not essential, permanent entities but **contingent configurations of probability**, subject to the logic of chance. In doing so, *Impossible Probability* situates statistical reasoning firmly within a dialectical ontology of randomness.

53.13. Random Necessity and Scientific Policy

From the dialectical perspective, *the only necessity governing all that occurs is* ***random necessity****:* everything happens necessarily in a random manner. Beyond this fundamental necessity, any other form of necessity invoked by science is a matter of **scientific policy**.

Scientific policy introduces additional forms of necessity by articulating objectives and goals within the framework of **critical reason**. These goals embody the ideals of science—such as truth, reliability, and progress—and the ideals of humanity more broadly. In this way, political and ideological considerations define what kinds of necessity are recognized as binding within scientific practice.

Outside scientific policy, necessity remains random. Within scientific policy, necessity is ideological: it reflects the rational limits, margins of error, and ideals adopted at a given historical moment. Thus, random necessity governs empirical reality universally, while political necessity governs science specifically, anchoring it in the ideological project of humanity and science.

53.14. The Dialectical Definition of the Arithmetic Mean in the Second Method

Once the dialectical identity between statistics and probability is established, it becomes possible to define other dialectical identities—between subject and option, and between direct score and frequency.

This identity transforms the classical definition of the arithmetic mean. If direct score and frequency are no longer distinct but identical, the mean can no longer be defined

as the quotient of the sum of score × frequency over the total frequency. Instead, **new definitions emerge**: empirical probability and theoretical probability.

- **Empirical probability** represents the observed distribution of outcomes.
- **Theoretical probability** represents the ideal distribution of outcomes under equality of opportunities.

When theoretical probability is defined as the ideal statistic of equal-opportunity behavior, it assumes the function previously held by the arithmetic mean. Mathematically, this function is carried out by the **inversion of *N* (1/N)**. Thus, within the Second Method of *Impossible Probability*, the arithmetic mean is redefined as the theoretical probability of equality of opportunities.

53.15. The Difference Between Types of Samples

When the identities of direct score/frequency and subject/option are recognized, the relevant distinction shifts. ***It is no longer the difference between direct score and frequency that matters, but rather the difference between* types of samples**.

On one side, there is the **sample of subjects or options (N)**. On the other, there is the **sample of direct scores or frequencies (Σxi)**, where each "xi" represents either a direct score or a frequency.

This reorientation highlights that statistical reasoning depends less on the opposition between score and frequency than on the way the sample itself is defined. Different types of samples correspond to different definitions of reality, and therefore *lead* to different forms of statistical and probabilistic reasoning.

53.16. Application of the Second Method to the First Method

In section 12 of *Impossible Probability*, where the Second Method is applied to the First Method, the arithmetic mean of the First Method is redefined using the conceptual framework of the Second Method. Under this reformulation, the arithmetic mean is

equal to the **sample of direct scores or frequencies divided by the sample of subjects or options (N)**.

Thus, what the First Method regarded as the arithmetic mean of subjects or options becomes, under the Second Method, a measure situated within **statistical probability**. In other words, the arithmetic mean is no longer simply a descriptive measure but is reinterpreted as part of a broader probabilistic framework, linking it to both empirical and theoretical probability.

53.17. Theoretical Probability as the Arithmetic Mean of Empirical Probabilities

Within the Second Method of *Impossible Probability*, a fundamental distinction is drawn between **empirical probability** (based on observed outcomes) and **theoretical probability** (defined as the probability of occurrence under equal opportunity).

In this system, theoretical probability is calculated as the **average of all empirical probabilities**. Consequently, the **inversion of *N* (1/N)** simultaneously expresses two functions:

1. The **theoretical probability** of equal opportunity by chance.
2. The **arithmetic mean** of empirical probabilities.

This dual role underscores the dialectical nature of 1/N, which unifies empirical observation with theoretical ideality in a single mathematical expression.

53.18. Theoretical Probability as the Criterion of Randomness

Statistical theory is inherently **stochastic**, studying the random behavior of reality. Within this context, theoretical probability functions as the **criterion for determining whether a behavior is random or not**.

If a given behavior conforms to the principle of equal opportunity, it qualifies as **random behavior**, and in such cases the empirical probability tends to converge with the theoretical probability. The closeness of this convergence can be measured in various

ways, giving rise to the principal forms of rational critique employed in *Impossible Probability*.

These include:

- **Individual rational critiques**, such as *Validity of Equality* or *Significance of Equality*.
- **Sample-level rational critiques**, such as the *Critical Sample Level of Equality*.
- **Alternative methods of rational critique**, such as *Critical Proportions* (section 11), adaptations of the First Method (section 12), and **intermeditional critiques** of equality (sections 16–19).

Together, these procedures define the framework through which equality of opportunity is tested, not only in abstract theory but also in applied empirical contexts.

53.19. The Multifunctionality of the Inversion of *N*

In traditional statistics, the arithmetic mean is a **unidimensional statistic**, serving only to calculate the average of observed values. In *Impossible Probability*, however, the inversion of *N* acquires **remarkable multifunctionality**.

Specifically, 1/N simultaneously expresses:

- The **theoretical probability** of equality of opportunities by chance.
- The **arithmetic mean of empirical probabilities**, applicable to both finite and infinite universes.
- In infinite universes, additional functions such as:
    - The **probability of representativity error** in sampling.
    - The **probability of theoretical dispersion**.

This multifunctionality transforms 1/N into one of the central operators of *Impossible Probability*, integrating descriptive, probabilistic, and theoretical dimensions in a single expression.

53.20. Functions of the Inversion of *N* in Finite and Infinite Universes

Regardless of whether the universe under study is **finite or infinite**, the inversion of *N* serves as the **probability of behavior occurring by chance**.

The relationship is straightforward: the closer the **Bias Level** tends to zero, the greater the probability that behavior will exhibit randomness consistent with equal opportunity. At the same time, 1/N continues to serve as the **arithmetic mean of empirical probabilities**, ensuring that its function remains consistent across both finite and infinite contexts.

In this sense, the inversion of *N* becomes the pivotal statistic that bridges equality of opportunity, randomness, and the averaging function of empirical distributions, demonstrating the unification of statistical and probabilistic reasoning in *Impossible Probability*.

53.21. The Arithmetic Mean as a Function Performed by the Inversion of *N*

In this framework, the arithmetic mean—traditionally an equation of descriptive statistics—undergoes a profound transformation. Within statistical probability, or what *Impossible Probability* terms **the probability of probability**, the function of the arithmetic mean is now exercised by the **inversion of *N* (1/N)**.

This shift is not merely a mathematical substitution but reflects the **multifunctionality** that the inversion of *N* assumes in *Impossible Probability*. By redefining traditional concepts—such as sample, subject, option, direct score, and frequency—1/N takes on roles far beyond that of a simple average. It becomes simultaneously:

- a measure of equality of opportunities,
- the theoretical probability of chance behavior,
- the arithmetic mean of empirical probabilities,

- and, in infinite universes, a measure of sampling error and theoretical dispersion.

The redefinition of the arithmetic mean through 1/N provides the basis for **rational critique of what occurs**, allowing science to construct empirical and rational hypotheses, theories, models, and paradigms. In this sense, the reinterpretation of a seemingly simple statistic leads to a **qualitative shift in the epistemological foundations of science**.

In summary, by grounding itself in new definitions of classical concepts, *Impossible Probability* establishes that qualitative differences in statistical reasoning generate **significant qualitative and quantitative differences** in the political construction of science itself. The arithmetic mean thus ceases to be a purely descriptive tool and becomes a theoretical operator embedded in the dialectic of probability and statistics.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 17 March 2013,
Rubén García Pedraza
imposiblenever@gmail.com

54. Probability

54.1. Probability as a Rational Concept in Mathematics

Probability is fundamentally a rational construct designed to measure or quantify the degree of possibility of an event or phenomenon. It belongs to the field of mathematics, which may itself be understood as both a language and the study of that very language. Mathematics is widely employed across the sciences because it is perceived—at least in principle—to be free from subjectivism, offering a framework capable of providing highly precise and exact assessments.

For this reason, probability finds a privileged place in what are traditionally called the "exact sciences," such as physics, in certain forms of experimental modeling, and of course, in statistics and probability theory. Its role is central not only because it structures the language of scientific explanation but also because it underpins the possibility of quantifying uncertainty and making reasoned predictions.

54.2. Probability Theory as an Analytical Science

The study of probability necessarily leads to the development of probability theory, which belongs within mathematics but may also be classified as an **analytical science**. This classification follows from the fact that probability theory is concerned with the **formal analysis of relations**: relations between events, relations between phenomena, or even relations between other relations.

Probability theory does not study the material content of phenomena directly but rather their *structural relations* as expressed in formal terms. Its objective is thus not empirical description but the *logical and mathematical organization of possibility*. From this

standpoint, probability theory functions as one of the primary analytical frameworks for linking mathematics with the sciences.

54.3. Descriptive and Predictive Functions of Probability

Probability, understood as a mathematical ratio, quantifies the likelihood that a given event will occur. In this sense, probability may serve two simultaneous functions: **descriptive** and **predictive**.

- **Descriptive probability** refers to the measurement of empirical distributions. For example, in a given sample, the percentage associated with a particular behavior represents the probability of that behavior occurring within the sample. In this respect, relative frequencies—which in traditional statistics are simply percentages—take on the role of true statistical probabilities.
- **Predictive probability**, by contrast, is concerned with projecting possible outcomes. Historically, probability has been closely associated with games of chance, where it was used to calculate the likelihood of particular results. Over time, these techniques were extended into the sciences, where probability supports *predictions in domains ranging from meteorology to complex experimental designs*.

Thus, the dual functions of probability—description and prediction—mirror the dual functions of statistics: **descriptive statistics** (concerned with recording and summarizing what occurs) and **inferential statistics** (concerned with drawing generalizations from samples to larger universes). In both cases, inference implies the acceptance of a margin of error.

The relationship between probability and error may be summarized as follows:

- The **factual margin of error** (error de hecho) is the inverse of the sample size; the corresponding margin of reliability is therefore 1 minus this inverse.
- The **rational margin of error** (error racional) is determined by critical reason, often expressed as a chosen percentage of acceptable error (X%). In this case,

reliability is equal to 1 minus the critical reason. Conversely, if the margin is established on the basis of a percentage of reliability, then the error is equal to 1 minus this probability.

This framework makes explicit that all probabilistic reasoning is simultaneously a discourse of error and reliability.

54.4. Distinction Between Theoretical and Empirical Probability

Within the framework of *Impossible Probability*, the study of probability as applied to statistics is grounded in a **differentiation between theoretical probability and empirical probability**.

- **Theoretical probability** measures the likelihood of a possible event by comparing it to the totality of all possible events. It is the ratio of one event to the entire set of possible events. In conditions of equal opportunity—what may be termed the free will of what happens—the theoretical probability is expressed mathematically as the **inversion of N (1/N)**. This represents the probability that, out of *N* possible subjects or options, any one will occur *purely* by chance. In this sense, chance is defined as the equality of opportunities in the occurrence of events.
- **Empirical probability**, by contrast, arises when a set of *N* possibilities generates actual outcomes over time, *recorded* as direct scores or frequencies. The probability of each option is then calculated as its frequency (or score) divided by the sum of all frequencies (or scores).

Thus, while theoretical probability expresses the ideal distribution of possibilities, empirical probability *records the observed* distribution of outcomes. Together, they form the dialectical core of probabilistic reasoning in *Impossible Probability*.

54.5. Definition and Calculation of Empirical Probability

Empirical probability is defined as the **ratio of a specific score or frequency to the total sum of all scores or frequencies**.

- In studies of subjects, where each subject is associated with a direct score, the empirical probability of a subject is calculated by dividing its score by the sum of all scores in the sample.
- In studies of options, where each option has an associated frequency (the number of times it occurs), the empirical probability is calculated by dividing the frequency of that option by the total frequency of all options.

Traditional statistics referred to this calculation, in the case of frequencies, as **relative frequency**. However, in the framework of *Impossible Probability*, the concept is extended to encompass not only frequencies but also direct scores. Thus, empirical probability serves as a **universal definition**, applicable across all types of samples—whether they consist of subjects with scores or options with frequencies.

In this way, empirical probability generalizes the logic of relative frequency into a broader, dialectical conception of probability, one that applies equally to different universes of study.

54.6. Applications of Empirical Probability Across Different Universes

When the sample N consists of N **subjects** each associated with a **direct score**, the empirical probability of a given subject is computed as that subject's direct score divided by the **sum of all direct scores** in the sample (including its own).

When the sample N consists of N **options** each associated with a **frequency of occurrence**, the empirical probability of a given option is computed as that option's frequency divided by the **total frequency** across all options.

Whereas the classical notion of **relative frequency** is restricted to frequency-based samples, the concept of **empirical probability** is generalized to **any** sample of subjects or options. Thus, in universes of subjects the empirical probability equals *the subject's*

direct score divided by the sum of direct scores; in universes of options it equals *the option's frequency divided by total frequency*. To unify both cases:

$$\text{Empirical probability} = \frac{\text{direct score or frequency}}{\sum(\text{direct scores or frequencies})}.$$

This universalized definition allows a single probabilistic grammar to govern both measurement regimes, whether observations are registered as magnitudes (scores) or as counts (frequencies).

54.7. Descriptive and Predictive Value of Empirical Probability

Because empirical probability multiplied by one hundred yields a **percentage of empirical behavior**, it has both **descriptive** and **predictive** value. Descriptively, it summarizes how a subject or option behaves within the observed sample. Predictively, it offers an **objective forecast**—bounded by the *de facto* sampling error—of how that subject or option is expected to behave under the **same conditions** that generated the data.

Suppose a subject or option exhibits a given level of behavior in a study. Empirical probability describes that observed level and, ceteris paribus, supports a forecast that future behavior will align with the observed probability. Thus, empirical probability is not merely a snapshot of past outcomes; it is a calibrated indicator for **expectations** so long as the structural conditions of observation remain stable.

[In order to better understand the value of the empirical probability as a prediction value, we can use the Bias Level or any other relative statistics, or the difference with the Ideal Intermediate Probability ((1+0):2=0,5) to have a better idea about the real meaning of any single empirical probability]

54.8. Differences Between Universes of Subjects and Universes of Options

The distinction between **subject** and **option** mirrors the methodological distinction between **direct score** and **frequency**. In **universes of subjects**, we typically measure direct scores—magnitudes indexing some singular attribute of each subject. In **universes of options**, we measure the **number of occurrences** of each option, i.e., its frequency.

- In universes of subjects, the sample N equals the **number of subjects**, and the sum of all direct scores forms the **sample of direct scores**.
- In universes of options, the sample N equals the **number of options**, and the sum of all frequencies forms the **sample of frequencies** (the total frequency).

To **universalize** these definitions, we say: N is the sample of subjects or options; the denominator for empirical probability is either the sum of direct scores (subject-universes) or the sum of frequencies (option-universes). Hence, for any subject or option:

$$p_{\text{emp}} = \frac{\text{direct score or frequency}}{\sum(\text{direct scores or frequencies})}.$$

This harmonized formulation provides a single probabilistic rule across heterogeneous data structures.

54.9. Infinite Universes and Limited Universes

Within *Impossible Probability*, universes of **subjects** are often termed **infinite universes** (or universes of subjects/options infinite), whereas universes of **options** are termed **limited universes**. The rationale is methodological: in subject-universes we extend to subjects the treatment that classical statistics reserved for options, thereby opening the door to potentially **unbounded** refinement of measurement and partition.

Calling subject-universes "infinite" does not claim literal boundlessness in every context; rather, it highlights the **open-endedness** of sampling and subdivision that subject-based measurement admits (e.g., continuous scores, indefinitely fine-grained partitions), in contrast with the **a priori bounded** set of options defined in limited universes.

54.10. Extending Relative Frequency to Empirical Probability

Classically, **relative frequency** applies to option-studies, computed as the option's frequency divided by total frequency. **Empirical probability** generalizes this same mathematical treatment to **subject-studies** with direct scores: the subject's empirical probability equals its **direct score divided by the sum of all direct scores**.

This extension justifies labeling subject-universes as "universes of subjects or options infinite": the relative-frequency logic is **lifted** from discrete options to continuous or graded subject measurements. As a result, the same probabilistic syntax governs both discrete-choice contexts and continuous-score contexts, unifying statistical practice under a single, empirically grounded definition of probability.

54.11. Time and the Inevitability of Possibilities

One of the most important characteristics of probability theory in *Impossible Probability* is the repeated insistence that, given sufficient or infinite time, **every**

possibility becomes inevitable. Imagine, for example, a casino that remains open forever. In such a case, any possible outcome of the roulette wheel—or any other game of chance—will eventually occur. The crucial question is not *whether* a given combination will appear, but *when*. If we dispose of infinite time, it is self-evident that every combination will eventually be realized.

This framing highlights a central thesis: probability is not only a mathematical ratio but also a **temporal function**. When we place a bet on any option—whether in a lottery, a game of chance, or even in the unfolding of life itself—it is absolutely inevitable that the option, including ours, will occur, provided two conditions hold: the principle of free will in equal opportunities (chance) and the availability of sufficient time. Thus, the realization of an outcome is purely a matter of temporal sufficiency. If infinite time is granted, then everything that is logically coherent [if the conditions of possibility have been previously designed or naturally created] becomes not merely possible but inevitable.

[The key here is the conditions of possibility. In the time of Alexander the Great, war was fought on horseback rather than with cyborg robotics. Alexander the Great might have had a profound understanding of Aristotelian philosophy and the concept of the *tabula rasa*, but he could not have possessed the technological knowledge of brain–machine interfaces that we now have in London. What was impossible in ancient times is, in London today, unavoidable.

Naturally, one might consider the impossibility of a supervolcano or a massive earthquake in England. However, if there were a major shift in tectonic plates — for instance, if this side of the Atlantic Ocean began subducting beneath the North American Plate along the Mid-Atlantic Ridge — London could, in theory, collapse beneath the overriding American plate.]

54.12. The Infinite Universe as a Temporal Definition

The reason why the universe of subjects is referred to as an **infinite universe of subjects or options** lies in the inherently **temporal definition of probability**. Since

probability is structured as a temporal function, in a sufficiently extended or infinite time span, every possibility will eventually occur. Consequently, subjects and options may be regarded as infinite—not necessarily in quantity at a given moment, but in their potential manifestations across infinite time.

The only limitation arises if the population itself disappears, leading to extinction. If extinction occurs, then the universe of subjects collapses. However, even in such a case, given any finite population within a finite period, the possibility of **infinite subdivisions of space-time** persists, allowing for infinitely many measurements within a bounded temporal framework. Thus, infinitude is understood not merely as an endless extension, but also as an **unbounded divisibility** of empirical reality.

54.13. Conceptions of Infinity

Infinity can be understood in two principal ways. The first is an **infinity defined by the absence of limits [the ideal of no beginning and no ending point]**, **or there is only one unbounded dimension, for example, an infinite continuum may have a beginning but no end—thus infinite in one direction but finite in another**. The second is an **infinity defined by infinite divisibility [Zeno's paradoxes]** between two boundaries, such that within any finite interval there exists an unending series of subdivisions.

In both cases, infinity provides a mathematical and philosophical framework for probability: whether conceived as boundlessness or divisibility, infinity guarantees the possibility of generating **infinitely many direct scores or frequencies**, and hence, an inexhaustible field of probabilistic analysis.

[The idea of the infinite subdivision of time and space is another antinomy: there are as many arguments against it as there are in favor of it.]

54.14. Universes of Limited Options

In contrast, a **universe of limited options** is defined as a **finite universe**, where the number of possible outcomes is constrained by the very hypothesis of the study. Thus, in limited universes, the boundary conditions are built into the hypothesis itself. The definition of the study establishes a finite set of possible outcomes, and probability is calculated strictly within this circumscribed framework. The limitation can be **material** (determined by physical constraints) or **social** (determined by normative or conceptual frameworks), [Or it may be due to scientific policy, as in the case of discrete categories. We must also take into account limited technological universes, especially given that AI is advancing very rapidly. An example of how fast AI can escalate at very high speed is London right now]

54.15. Examples of Universes of Limited Options

Consider a coin toss: by definition, there are only two material outcomes—heads or tails. This is a paradigmatic case of a universe of limited options. Similarly, in a social study, one may hypothesize that within a randomly selected sample there will be a slightly higher probability of one type of attitude compared to another. Here, the attitudes under consideration are themselves the **options of the frequency distribution**, and they are already limited by the hypothesis.

Thus, universes of limited options are those where the possible outcomes are explicitly defined in advance. Whether in physics (e.g., dice throws, coin flips) or in sociology (e.g., survey responses), the logic of limitation rests upon the fact that the study specifies in advance the **set of admissible alternatives**. These delimitations ensure that probability calculations are both meaningful and bounded within the scope of the research design.

54.16. Types of Universes of Limited Options

Within the framework of limited-option studies, it is necessary to distinguish between **two principal types of universes of options**: those that are **materially limited** and those that are **socially limited**.

In materially limited universes, the restrictions arise from the **physical or natural boundaries** of reality itself. For instance, the possible outcomes of rolling a six-sided dice are inherently restricted to the integers 1 through 6. No additional options exist because the material configuration of the die excludes them.

By contrast, socially limited universes are defined by **normative, institutional, or conceptual boundaries**. Here the set of possibilities is constrained not by physical necessity but by human construction—social agreements, linguistic frameworks, or methodological decisions. For example, in a sociological survey where participants are asked to classify their political orientation into five predefined categories, the universe of options is socially bounded, even though in practice the spectrum of political orientations may be more complex and fluid.

Thus, the **type of limitation—material or social—determines the structure of the probabilistic universe** and guides the manner in which probability is calculated. This distinction reinforces the central principle of *Impossible Probability*: that definitions of universes are not merely descriptive but carry epistemological and ideological consequences.

54.17. Final Synthesis: Probability as Mathematical Ratio and Dialectic

In synthesis, **probability is fundamentally a mathematical ratio**, a tool designed to quantify the degree of possibility that a given event may occur. While its origins lie in classical probability theory, its conceptual and methodological scope has expanded, allowing for **new theoretical developments**. One such development is the framework proposed in *Introduction to Impossible Probability* (founded mathematically on October 16, 2002), which articulates the distinction between **theoretical probability** and **empirical probability**.

This distinction is not arbitrary; it emerges from the deeper **dialectic between direct scores and frequencies**, which itself derives from the more fundamental **dialectic between subject and option**, rooted ultimately in the classical philosophical dialectic of **subject and object**. In this sense, the *statistics of probability* or *probabilistic statistics* elaborated in *Impossible Probability* represents a logical application of dialectical reasoning to the mathematical domains of probability and statistics.

The final synthesis is that probability is not only a quantitative tool but also a **dialectical mediator between empirical variability and theoretical universality**. It simultaneously operates within the realm of measurable occurrences and within the rational frameworks that structure our interpretation of chance, necessity, and possibility.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 24 March 2013,
Rubén García Pedraza
imposiblenever@gmail.com

55. Mean Absolute Deviation and Standard Deviation

55.1. Empirical dispersion: Mean Absolute Deviation, Standard Deviation, and Variance

The **Mean Absolute Deviation (MAD), [or simply Mean Deviation (MD)]** and the **Standard Deviation (S)**, together with the **Variance (S^2)**, belong to the family of **dispersion statistics** in descriptive statistics—those statistics that quantify the **empirical spread** of a sample. In the traditional approach, the computational pathway runs from the mean absolute deviation to the variance and then to the standard deviation: one first computes the mean-centered differences, then (optionally) squares and averages them to obtain the variance, and finally takes the square root to obtain the standard deviation. We begin with this **classical framework**, and subsequently reinterpret these measures within the lens of **statistical probability** as articulated in *Impossible Probability*.

At bottom, both MAD and S measure how far, **on average**, individual observations lie from the sample's **central tendency**. In the classical setting that central tendency is the **arithmetic mean**; dispersion is thus conceptualized as the average distance of each observation from that mean.

55.2. Arithmetic mean and mean-centered (differential) scores

In traditional statistics the overall average of the sample is the **arithmetic mean**, computed (for grouped data) as the ratio between the **sum over categories of value × frequency** and the **total frequency**. Here, a **direct score** is the measured value

attached to an observational unit, while the **frequency** records how many times that value appears.

The arithmetic mean is a **measure of central tendency**: it locates the "center" toward which the observations cluster. By contrast, the mean absolute deviation and the standard deviation are **measures of dispersion**: they quantify the average **distance** (or difference) of each observation from that central tendency.

Operationally, to measure average distance one first forms **mean-centered (differential) scores**: for each direct score "xi", compute

$$d_i = x_i - \bar{x},$$

where $\bar{x}$is the arithmetic mean. These $d_i$represent the signed distances of the observations from the mean and constitute the raw material for dispersion measures.

55.3. Computing the Mean Absolute Deviation (absolute values)

With the differentials d_i in hand, classical descriptive statistics defines three related measures of dispersion: **MAD**, $\mathbf{S^2}$, and **S**. The **Mean Absolute Deviation** is obtained by averaging the **absolute** differentials (for ungrouped data) or, for grouped data, by dividing the **sum over categories of absolute differential × category frequency** by the total frequency:

$$\text{MAD} = \frac{\sum f_i \mid d_i \mid}{\sum f_i}.$$

Why absolute values? Because if one were to sum the **signed** differentials d_i, negative deviations below the mean would cancel positive deviations above the mean. Since the

mean is a balancing point, by construction; hence a naïve average of signed differentials would be zero and therefore **uninformative** about spread. Taking absolute values preserves **magnitude** while discarding sign, yielding a meaningful average distance from the mean.

55.4. Variance and the sign–cancellation problem

Some classical treatments regard the use of absolute values as **less tractable** analytically (e.g., for algebraic manipulation, differentiation, and distributional theory). To avoid sign cancellation **and** maintain algebraic convenience, the standard solution is to **square** all differentials:

$$\text{Variance} = \frac{\sum f_i \, d_i^{\,2}}{\sum f_i}$$

Squaring converts all contributions to **nonnegative** values and penalizes larger deviations more heavily, producing a strictly positive measure (except in the degenerate case of zero spread). In short, **variance** solves the sign-cancellation problem while delivering a measure that is mathematically well-behaved for further analysis (e.g., in the normal model, least squares, or the central limit theorem).

55.5. Standard Deviation and the Standard Score (z-score)

Although variance is analytically convenient, it is expressed in **squared units** of the original variable, which complicates direct interpretation and ratio comparisons with **unsquared** quantities (such as the raw differentials d_i). The **Standard Deviation** restores the original scale by taking the square root of the variance:

$$S=\sqrt{S^2}$$

With SD (Standard Deviation, S may be symbolized as SD) and the mean-centered differentials in the **same units**, one can construct the **standard score** (or **z-score**), a unit-free index of relative deviation:

$$z_i = \frac{x_i - \bar{x}}{\text{SD}} = \frac{d_i}{\text{SD}}.$$

The z-score expresses how many **standard deviations** an observation lies **above** (positive) or **below** (negative) the mean. This normalization is crucial for (i) comparing dispersion-adjusted positions across variables and studies, and (ii) linking observed values to **areas under reference distributions** (e.g., the normal curve) for **hypothesis testing**, **confidence assessment**, and **error-area** reasoning. In this way, the path *differentials* → *variance* → *standard deviation* → *z* provides a coherent bridge from descriptive spread to inferential evaluation.

55.6. An alternative framework: Statistical Probability (*Impossible Probability*)

In contrast to the **traditional model** of explaining Mean Absolute Deviation (MAD) and Standard Deviation (SD), *Impossible Probability* proposes an **alternative interpretative framework**. This approach, developed within the broader theoretical architecture of **statistical probability**, does not discard the traditional definitions but **reorients and complements them** by systematically adjusting statistical concepts to the logic of probability theory—or, conversely, by reshaping the foundations of probability through statistical categories.

In this framework, a **clear distinction** is drawn between two empirical bases of measurement:

- **Subjects**: elements taken from a universe of subjects, where each subject yields a **direct score** (for instance, the measured intensity of a characteristic).
- **Options**: elements from a universe of options, where what is measured is the **frequency** of occurrence of each option (e.g., the number of times an event is observed).

From **samples of subjects**, one obtains a set of direct scores; from **samples of options**, one obtains a distribution of frequencies. Yet regardless of whether we are working with subjects or options, the general definition of **empirical probability** remains the same:

$$p(x_i) = \frac{x_i}{\sum x_i},$$

Where N denotes the number of subjects or options, xi the direct score (for a subject) or the frequency (for an option), and p(xi) the **empirical probability** associated with that subject or option. This equation provides the foundation for all further dispersion measures within *Impossible Probability*.

55.7. Empirical probability and theoretical probability (1/N)

Opposed to empirical probability stands **theoretical probability**, formally defined as the **reciprocal of the sample size**:

$$\text{Theoretical probability} = \frac{1}{N}.$$

This represents the **probability of equal opportunity by chance**, where “chance” is understood as the **free unfolding of events under conditions of equality of**

opportunity. A model is said to be *fully random* when **no empirical bias** distorts the distribution—i.e., when every subject or option has the **same probability**.

To illustrate, consider an **educational setting**. If an instructional system truly guarantees equality of opportunity—through remedial measures, compensatory pedagogy, and equitable access to learning—then at the final evaluation, all students would ideally attain the **same level of mastery**. In this model, each student (subject) would achieve the same direct score. Consequently, their **empirical probabilities of success** would be identical and, collectively, would coincide with the **theoretical probability**:

$$p(x_i) = \frac{1}{N}.$$

This expression shows that, under conditions of perfect equality of opportunity, the empirical distribution aligns exactly with the theoretical model of **chance-based fairness**.

55.8. Subjects and options: examples and universes

In *Impossible Probability*, the notion of **subject** extends beyond the human individual. A **subject** is defined broadly as **any entity that can serve as the bearer of a measurable predicate**. Thus, a statistical subject could be a person, an organism, an artifact, or even a natural object, provided that one can assign a measurable direct score to it and, from that, derive an empirical probability.

By contrast, an **option** is characteristic of **stochastic models with limited alternatives**. Here, one measures the **frequency** of each option's occurrence. For instance, in an **electoral process**, each candidate represents an option, and each vote is a frequency count. The probability of success for a candidate equals their vote count divided by the total number of votes. Crucially, in such universes, the objective is not equality of opportunity but rather to maximize **positive bias** (i.e., the candidate with the greatest relative advantage).

From this distinction arises the classification of universes:

- **Universes of subjects** are potentially **infinite**, since—over infinite time—the number of subjects (measurable entities) can grow without bound.
- **Universes of options** are typically **finite or limited**, since they are constrained by the defined set of possible alternatives (e.g., candidates in an election, outcomes of a coin toss).

55.9. Types of study and internal references

Within *Impossible Probability*, empirical studies are categorized according to their **objectives**:

- **Equality of opportunities**, where the aim is to verify whether empirical probabilities approximate the theoretical ideal ($1/N$).
- **Positive bias**, where the goal is to maximize an advantageous deviation.
- **Negative bias**, where the aim is to minimize undesirable outcomes (e.g., reducing symptoms in a medical trial).

As an example, consider a study involving N patients, each measured for the severity of a particular symptom. The **ideal outcome** would be a maximization of negative bias: symptom levels tending toward zero.

For a comprehensive treatment of these different study types, *Introduction to Impossible Probability* directs readers to **Section 9** (on universes of options), **Section 10** (on universes of subjects), and **Section 11** (on rational critique models). These sections provide the theoretical scaffolding necessary to classify, interpret, and critique empirical studies within this alternative probabilistic-statistical framework.

55.10. Mean of empirical probabilities and the inversion of N

When addressing the Mean Absolute Deviation or Standard Deviation from the standpoint of *Impossible Probability*, one begins with the premise that, in any sample (whether of subjects or options), the **empirical probability** is defined as:

$$p(x_i) = \frac{x_i}{\sum x_i}.$$

If one then computes the **arithmetic mean of these empirical probabilities**, an interesting result follows. Since the sum of all empirical probabilities equals unity ($\sum p(x_i) = 1$), dividing this sum by the sample size N yields:

$$\text{Arithmetic mean of empirical probabilities} = \frac{\sum p(x_i)}{N} = \frac{1}{N}.$$

Thus, the inversion of N ($1/N$)—already recognized as the theoretical probability of equal opportunity—also emerges naturally as the **arithmetic mean of the empirical probabilities**. This dual role highlights the **multifunctionality** of 1/N: it simultaneously represents a **theoretical principle of chance-based fairness** and a **descriptive statistical mean**.

In this way, *Impossible Probability* integrates central concepts of dispersion into a **dialectical synthesis**: traditional descriptive statistics are reinterpreted so that **the empirical and theoretical converge at 1/N**, linking probability, equality of opportunity, and measures of central tendency into a single unifying expression.

55.11. Level of Bias and Total Bias

Since the inversion o N simultaneously assumes the role of **theoretical probability** and the **arithmetic mean of empirical probabilities**, what traditional statistics would call the *differential score* is reconceptualized in *Impossible Probability* as the **Level of Bias** (*Nivel de Sesgo*).

This measure expresses the **deviation of each empirical probability from the theoretical probability 1/N**. Formally, the *normal Level of Bias* of a subject or option is defined as:

$$\text{Level of Bias (normal)} = p(x_i) - \frac{1}{N}.$$

The Level of Bias therefore represents the **individual dispersion**—the deviation of each empirical probability from the theoretical baseline of equal opportunity.

It is called *normal* to distinguish it from **relative Levels of Bias**, which measure deviation not from the theoretical probability, but from other empirical benchmarks (e.g., the maximum, minimum, or intermediate empirical probability). Relative bias calculations allow for alternative descriptive statistics, but the *normal Level of Bias* (empirical minus theoretical) serves as the standard baseline.

Once the normal Level of Bias is computed for each subject or option, the **Total Bias** is obtained by summing the **absolute values** of all bias levels:

$$\text{Total Bias} = \sum \left| p(x_i) - \frac{1}{N} \right|.$$

This ensures that positive and negative deviations do not cancel each other, providing a valid measure of the **overall magnitude of dispersion** within the sample.

55.12. Mean Deviation Based on Bias Levels

After computing the Level of Bias for each subject or option, one can define the **Mean Deviation (DM, *Desviacion Media*, in Spanish)** of empirical probabilities as the **Total Bias divided by the sample size N:**

$$\text{Total Bias} = \sum \mid p(x_i) - \frac{1}{N} \mid.$$

Here, while the Level of Bias provides a **measure of individual dispersion**, the Mean Deviation serves as a **sample-wide empirical dispersion measure**.

It is necessary to work with absolute values because, by the **law of chance compensation**, the sum of positive and negative deviations from the theoretical probability tends to cancel out to zero. Without absolute values, the mean deviation would always collapse to zero, obscuring the true degree of dispersion.

The principle underlying this adjustment is that **positive and negative biases are symmetrically distributed in the long run**: chance ensures that excesses in one direction are balanced by deficits in the other. Thus, dividing the Total Bias by two yields the **Maximum Empirical Bias Possible**, a concept elaborated further in section 55.13.

55.13. Maximum Empirical Bias Possible

The **Maximum Empirical Bias Possible** represents the **upper bound of deviation** that a single subject or option can achieve within a sample.

For example, suppose that within a set of N subjects or options, **only one** is “ideal” (positively biased) while all others are negatively biased. In that case, the positive bias of that single subject equals half the Total Bias:

$$\text{Maximum Empirical Bias Possible} = \frac{1}{2} \times \text{Total Bias.}$$

The same holds symmetrically: if only one subject or option carries negative bias and all others positive, the negative bias of that element equals the maximum possible. This formulation allows *Impossible Probability* to capture extreme scenarios of **empirical asymmetry**, providing a ceiling against which other dispersion measures can be compared.

55.14. Variance, Standard Deviation, and Typical Score (z-score) in Bias Terms

To align the statistical probability framework with **traditional statistics**, one can square the Levels of Bias. This eliminates the sign problem while avoiding absolute values, yielding a quadratic dispersion measure:

$$S^2 = \frac{\sum(p(x_i) - \frac{1}{N})^2}{N}.$$

This is the **Variance**, reinterpreted as the quadratic average of bias levels.

Taking the square root returns the **Standard Deviation (S):**

$$S = \sqrt{\frac{\sum(p(x_i) - \frac{1}{N})^2}{N}}.$$

This measure allows comparison between **individual dispersion (bias level)** and **sample dispersion (standard deviation)**. The ratio is known as the **Typical Score** or **z-score** in this framework:

$$\text{Typical Score} = \frac{p(x_i) - \frac{1}{N}}{S}.$$

This establishes a direct bridge between the *Impossible Probability* framework and conventional statistical inference, while still grounding the analysis in the **dialectic of empirical vs. theoretical probability**.

55.15. Preference for Mean Deviation over Standard Deviation

In traditional statistics, the Standard Deviation is often favored over the Mean Deviation as the default measure of dispersion. *Impossible Probability*, however, argues for the **greater objectivity of the Mean Deviation**.

The reason is methodological: the Standard Deviation involves quadratic and square root transformations, which **distort the data**. These transformations not only change the scale of dispersion but may also introduce **loss of information**, particularly when decimal truncation occurs in square root operations. By contrast, the Mean Deviation works directly with **untransformed differences**, preserving the empirical structure of the data.

The Mean Deviation is thus interpreted as the **average bias level**, providing a more **transparent and precise representation of empirical dispersion**. For this reason, *Impossible Probability* recommends the Mean Deviation as the preferred measure, while still allowing the Standard Deviation to be used at the discretion of the **scientific policy framework** governing the study.

This reflects the underlying epistemology of *Impossible Probability*: statistical choices are not merely technical but also involve **philosophical commitments** to precision, transparency, and the dialectical reconciliation of empirical and theoretical truth.

55.16. Individual, Empirical Sample, and Theoretical Sample Dispersion

The reason why the Mean Deviation (DM) and Standard Deviation (SD) are regarded as measures of **empirical sample dispersion** is that they capture the **central tendency of the variability** present within the sample. In other words, they provide an estimate of the *average degree of empirical dispersion* of the data.

When one emphasizes that DM and SD are sample-level measures, it becomes clear that they stand in contrast to two other forms of dispersion: (a) **individual dispersion**, represented by the Level of Bias for each subject or option, and (b) **theoretical sample dispersion**, which is derived from mathematical expectations rather than empirical observation.

Thus, DM and SD quantify dispersion at the level of the entire dataset, while the Level of Bias measures dispersion at the individual level. The relationship between the two is formalized through the **Typical Score (z-score)**, which compares individual dispersion to overall sample dispersion:

$$\text{Typical Score} = \frac{\text{Level of Bias}}{DM \text{ or } SD}.$$

In *Impossible Probability*, DM and SD are explicitly identified as empirical sample dispersion measures because they are constructed on the basis of empirical deviations (Levels of Bias), while also being set against a backdrop of theoretical dispersion.

55.17. Theoretical Sample Dispersion: Inversion of the Sample

While DM and SD are **empirical indicators**—derived from observed differences between empirical and theoretical probabilities—the notion of **theoretical dispersion** is expressed through the **inversion of the sample**.

If DM and SD are the empirical probability of dispersion in the sample, then theoretical dispersion is defined as the inversion of the sample.

with the exact form depending on the type of universe under study.

- In **universes of subjects** (where each subject carries a direct score), the theoretical sample dispersion equals the inversion of N , i.e., 1/N. This reflects the principle that as sample size grows, individual variations cancel out, producing a distribution that converges on the center of the Gaussian curve.
- Conversely, in **universes of options** (where occurrences are counted as frequencies), the theoretical dispersion is given by the inversion of the sum of frequencies, 1/Σxi. This formulation recognizes that the probability of observing dispersion diminishes as the total number of occurrences increases.

Thus, theoretical dispersion operates as a **structural benchmark**—the expected variability based on sample magnitude, against which empirical dispersion can be compared.

55.18. Universes of Subjects and Universes of Options

In universes of subjects, sometimes called **infinite universes** (because subjects are treated as options and their number can be indefinitely extended in infinite time), the theoretical probability of dispersion is defined as:

$1/N =$ theoretical probability of dispersion in universes of subjects or infinite options.

The larger the sample N, the closer subjects cluster around the mean, reducing dispersion. Conversely, smaller samples produce higher variability. Hence, **theoretical dispersion is inversely proportional to sample size**.

In universes of options—**limited universes**, where the possible alternatives are bounded—the theoretical probability of dispersion is defined as:

$$1/\Sigma x_i = \text{theoretical probability of dispersion in universes of limited options.}$$

Here, each occurrence contributes to the total frequency, and as the number of occurrences grows (e.g., repeated coin tosses), empirical probabilities tend to converge toward the theoretical ones. In the absence of bias, the more repetitions, the lower the theoretical dispersion.

Therefore, the distinction is clear:

- **Infinite universes (subjects):** theoretical dispersion = $1/N$.
- **Limited universes (options):** theoretical dispersion = $1/\Sigma x_i$.

55.19. Theoretical Randomness ($1/N$) and Empirical Randomness (DM/SD)

At the same time, DM and SD are not merely dispersion measures—they also function as indicators of **empirical randomness**.

- **Theoretical randomness** is captured by the inversion of N, 1/N, which expresses the probability of occurrence under pure equality of opportunity (absence of bias). This is randomness as a theoretical construct.
- **Empirical randomness** is measured by DM or SD, which quantify how randomness actually manifests in the distribution of observed biases.

Formally, DM can be expressed as the Total Bias multiplied by the theoretical randomness 1/N. Thus, DM embodies randomness **as it appears empirically in the sample**:

$$DM = \text{Total Bias} \times \frac{1}{N}.$$

In this sense, DM and SD can be read as **"bias by chance" or "chance by bias"**, highlighting their dual role as descriptors of how randomness interacts with systematic deviation.

55.20. Theoretical Maxima of Dispersion and Sample-Level Rational Criticism

Impossible Probability extends the analysis further by introducing the notion of **theoretical maxima of dispersion**, which serve as reference points for rational criticism of empirical hypotheses.

These maxima include:

- **Maximum Theoretical Mean Deviation Possible**, defined as the highest DM achievable under conditions where only one subject or option is ideal (probability = 1) and all others are non-ideal.
- **Maximum Theoretical Variance Possible**, derived from the same condition but in quadratic form.
- **Maximum Theoretical Standard Deviation Possible**, as the square root of the maximum variance.

Such maxima are indispensable for **sample-level rational criticism**. For instance, they inform the *Critical Sample Level of Equality* or the *Critical Sample Level of Bias*, depending on whether the study aims to test equality of opportunities or to measure the degree of systematic bias (positive or negative).

These theoretical boundaries also underpin the **omega models**, where the empirical dispersion (DM or SD) is compared against its theoretical ideal.

In summary, while traditional statistics provide useful tools for describing empirical variation, *Impossible Probability* situates dispersion within a **dialectical framework**, contrasting empirical and theoretical, individual and collective, randomness and bias. This duality allows for a richer, more critical evaluation of hypotheses in both finite and infinite universes.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 31 March 2013,
Rubén García Pedraza
imposiblenever@gmail.com

56. Statistics

56.1. The Analytical and Stochastic Nature of Statistics

Statistics has traditionally been classified as a mathematical discipline. At the same time, however, for many other sciences it functions as a method of study. Since mathematics itself is an **analytical science**, statistics must also be understood in analytical terms. It is primarily concerned with the study of formal relationships between facts or phenomena, within a delimited extension of space and time.

What distinguishes statistics from other forms of analytical inquiry is that its subject matter is of a **stochastic nature**. That is, statistical phenomena occur within contexts that involve sequencing or ordering of events, where results are in some measure dependent on chance, given that there is no absolute causal determination. In this sense, statistics combines the rigor of mathematics with the probabilistic uncertainty inherent to real-world processes.

56.2. Pure and Applied Research in Statistics

Traditional epistemology drew a line between **pure research** and **applied research**. Pure research was directed toward the internal development of a discipline itself, while applied research concerned the implementation of scientific knowledge in other fields.

This distinction is also relevant for statistics. On the one hand, **pure statistical research** focuses on the growth of the discipline itself, its internal theories, and its understanding of stochastic structures. On the other hand, **applied statistical research** extends beyond disciplinary boundaries, functioning as a **heuristic method** of inquiry for the synthetic sciences. In this applied role, statistics ceases to be merely

a branch of mathematics and becomes an instrument for constructing and testing knowledge in the natural and social sciences [and technological research].

56.3. The Dual Dimension of Statistics

If we follow this classical division between pure and applied research, statistics reveals itself to have a **dual dimension**.

- As a **discipline for itself**, statistics belongs to the analytical domain of mathematics. Its purpose here is to develop theories that explain its stochastic nature and refine the internal logic of statistical reasoning.
- As a **method for other sciences**, statistics functions as a tool of empirical inquiry, assisting in the generation of synthetic theories of reality. In this role, it becomes a method of discovery and justification, enabling scientists to move from raw data to structured explanations of natural or social phenomena [or testing novel cutting edge technologies].

Thus, any definition of statistics must take into account this double aspect: statistics is simultaneously a **discipline in itself** and a **heuristic method of study for other sciences**.

56.4. Statistics as Theory versus Statistics as Method

From this dual perspective, two possible definitions of statistics emerge.

1. **Statistics as a mathematical discipline**: In this sense, statistics belongs to the analytical sciences, and it is rightly *integrated into the mathematics curriculum at every educational level*. This definition stresses its formal and theoretical dimension, grounded in logic and probability theory.
2. **Statistics as a heuristic method**: In this sense, statistics becomes a form of applied science. It serves the purpose of generating synthetic data and theories in other fields, such as biology, economics, psychology, or sociology. Here, the

focus is on its capacity to help us **understand empirical reality** by organizing, summarizing, and interpreting data.

Both definitions are valid, and their coexistence is precisely what gives statistics its unique position within the sciences.

56.5. Pure Research and the Development of Statistical Theory

When statistics is approached as an **analytical discipline**, its development depends on pure research. The outcome of such research is the elaboration of statistical theory itself.

An example of this can be found in *Impossible Probability*, where a whole theoretical framework is constructed concerning the **statistics of probability**—that is, the application of statistical methods to probability and vice versa. This approach expands the boundaries of the field and redefines the relationship between mathematics, statistics, and epistemology. In such works, statistics is not just a tool but a self-developing discipline, capable of producing new theoretical horizons.

56.6. Applied Research and the Heuristic Function of Statistics

When statistics is applied to other sciences, it becomes a **heuristic method**. In this role, it is not the internal theory of statistics that is being advanced, but rather the capacity of other sciences to build **synthetic theories** of their own subject matter.

In natural sciences, such as physics or biology, applied statistics allows the formulation of generalizations about natural laws based on empirical data. In the social sciences, it provides the foundation for analyzing human behavior, economic systems, or cultural patterns. Thus, applied statistics is essential for the empirical grounding of both natural and social sciences [and technological development].

56.7. The Epistemological Position of Statistics

Within its dual definition, the place of statistics depends on whether it is understood as a **discipline** or as a **method**.

- If defined as a **discipline**, statistics belongs within mathematics, where it has traditionally been located and taught.
- If defined as a **method**, statistics belongs to **epistemology**, the science of knowledge and scientific methods. In this case, statistics is ***classified*** as one among many heuristic tools by which sciences **investigate** reality.

This dual belonging makes statistics an ambivalent field: *simultaneously* part of mathematics and part of epistemology. It embodies the tension between **formal analytical reasoning** and **practical methodological application**.

56.8. The Ambivalent Classification of Statistics

The result of this analysis is a **double classification** of statistics.

- As a **mathematical discipline**, it is an analytical science focused on internal theoretical development.
- As a **scientific method**, it is an epistemological tool, applied heuristically to other sciences for the purpose of constructing theories about reality.

Therefore, statistics occupies a unique position in the hierarchy of sciences. It belongs both to the formal world of mathematics and to the methodological world of epistemology, reflecting its dual capacity to **create its own theory** and to **enable the creation of theory in other fields**.

56.9. The Double Definition of Statistics: Mathematics or Epistemology

Within the dual definition of statistics—whether as a **mathematical discipline** or as a **method of epistemology**—the ultimate definition depends on the final sense or purpose of research. If the aim is **pure research** into the internal mathematical logic of formal statistical relations, then statistics reveals its analytical essence, as explained particularly in the opening sections of *Introduction to Impossible Probability: Statistics of Probability or Statistical Probability*. Here, the profoundly analytical nature of statistics becomes evident, since its foundation lies in the very logic of relations.

By contrast, if the ultimate goal of research is the **synthetic study** of phenomena, then statistics operates primarily as a **heuristic method**. In such cases, its role is not to deepen its own logical-mathematical basis but to provide methodological support for sciences concerned with constructing synthetic explanations of empirical reality.

56.10. Pure Research in Statistics and Pure Research in Epistemology

Since statistics can be defined either as a **mathematical discipline** or as an **epistemological method**, the scope of pure research also acquires a dual meaning. On the mathematical side, pure research in statistics seeks to **understand the logical relations** between statistical concepts themselves, derived from the formal study of relations among facts or phenomena.

Yet, statistics may also be framed within epistemology. In that case, one type of **pure epistemological research** consists in understanding statistics itself as a method for the synthetic sciences. This represents a different level of pure research, one that does not focus on the mathematical refinement of statistical concepts, but rather on building a theoretical foundation for how statistics, as a method, ought to be applied to empirical reality.

56.11. The Analytical-Mathematical and the Epistemological-Synthetic Functions of Statistics

This dual perspective leads to a broader understanding of statistics as having two primary functions:

1. **Analytical-mathematical**: Pure research in statistics is here directed toward clarifying the formal relations between statistical concepts. Its outcome is the *construction* of statistical theory as a logical and mathematical discipline.
2. **Epistemological-synthetic**: Pure research, in this sense, takes statistics as an object of epistemological study, asking how it can or should be applied to reality. Its result is the development of a **theory of epistemological application**, which clarifies how statistics should be *employed* as a heuristic method across different sciences.

When applied directly to natural or social facts [or technological testing], statistics functions as **applied research**, producing synthetic knowledge about empirical reality and thus enhancing our understanding of what actually happens.

56.12. The Mathematical Origin of Statistics and Its Passage into Epistemology

In any case, the origin of statistics lies in its **mathematical-analytical function**. Its beginnings are tied to the formulation of a pure mathematical-statistical theory. This is precisely the focus of *Introduction to Impossible Probability*, where the fundamental mathematical concepts of statistical probability are carefully fixed.

Once these concepts are firmly established, statistics can then take on a new role: it becomes part of the **heuristic methods of scientific investigation** and integrates into epistemology. In epistemological terms, statistics is no longer merely a discipline of formal relations but a **method of inquiry** designed for the study of synthetic sciences.

56.13. Epistemology and the Role of Statistics as a Scientific Method

Within epistemology, statistics is defined as a **scientific method** for investigating synthetic sciences. Epistemology itself studies the **degree of adequacy** of such methods in different fields of knowledge and evaluates their **reliability** when applied across the natural and social sciences.

Thus, while analytical-mathematical statistics is dedicated to pure research into its logical-mathematical foundation, epistemology undertakes a **pure methodological investigation**, assessing the appropriateness of statistics as a heuristic method in specific domains. This debate generates a broad spectrum of positions:

- At one extreme are **qualitative purists**, who reject the use of quantitative methods altogether, particularly in the social sciences.
- At the opposite extreme are **quantitative purists**, who argue that the only way to conduct reliable science is through quantitative methods in all fields, natural or social [and technological]. Within this quantitative paradigm, statistics often holds a position of preeminence.
- Between these extremes lies a wide variety of mixed approaches, combining qualitative and quantitative perspectives in different proportions.

56.14. The Position of *Impossible Probability* in the Qualitative-Quantitative Debate

The stance of *Impossible Probability* within this debate is that the apparent contradiction between qualitative and quantitative methods is **ultimately irrelevant**. Every measurement of empirical reality must begin with the assessment of the **singular qualities** of the particular subjects or objects under study, for which measurement scales are established.

From this perspective, the dialectical process shows that:

- The **qualitative** necessarily transforms into the **quantitative** (since qualities must be measured).
- The **quantitative** necessarily transforms into the **qualitative** (since numerical values must be interpreted in meaningful terms).

Therefore, every statistical study must integrate both: the **interpretation of statistical tables** and the **measurement of reality** as objectively as possible. However, in practice, such objectivity is extremely difficult—indeed impossible in the case of humanity—because the root of error lies in the **finitude of human perception** compared with the **infinite singularities of empirical reality**. Human beings can never fully comprehend 100% of reality; there will always be aspects that escape measurement, either due to their apparent insignificance or the inadequacy of methods. This generates an inevitable margin of error.

56.15. The Role of Scientific Policy in Statistical Interpretation

In this sense, the role of **scientific policy** is to determine which interpretative paradigm should be used for statistical data and to make the necessary decisions regarding their application. Scientific policy thus acts as the *mediator* between the methodological potential of statistics and its practical deployment in the pursuit of reliable knowledge.

56.16. Descriptive and Inferential Statistics

Whether defined as an analytical-mathematical discipline or as an epistemological method, statistics is traditionally *classified*—depending on its ultimate purpose—into two major branches:

- **Descriptive statistics**, which organizes and summarizes empirical data from a defined *sample*.
- **Inferential statistics**, which goes further, attempting to *generalize* from the sample to a wider population or universe of subjects.

In both cases, the starting point is a **series of facts or phenomena**, observed across a space and time previously delimited.

56.17. The Concept of the Sample in *Impossible Probability*

This series of facts or phenomena within defined spatial and temporal boundaries is called a **sample**. In *Impossible Probability*, two main types of samples are recognized:

1. The **sample of subjects or options**, symbolized as *N*.
2. The **sample of direct scores or frequencies**, symbolized as *Σxi*.

In any type of universe—whether **infinite universes of subjects or options** (where infinite qualities exist in empirical reality) or **limited universes of options** (restricted to a finite set of possible alternatives)—both types of samples are always obtained.

- The **sample of subjects/options (N)** provides the set of elements on which *measurements are taken*.
- The **sample of direct scores/frequencies (Σxi)** *records* the distribution of outcomes or occurrences.

Together, these two samples constitute the foundation of statistical analysis in *Impossible Probability*.

56.18. Population Studies and Infinite Universes of Subjects

Population studies fall within the category of **universes of infinite subjects or options**. This is because any population observed at a given point in history can only be understood as a **sample** of what is happening to that population across its entire historical development. A population is never static: it is part of a dynamic continuum, where individuals are born, die, migrate, or transform their social and natural conditions. Thus, any study of a population is necessarily limited, representing just one **temporal slice** of an infinite and ongoing process.

56.19. From Samples to Descriptive Statistics

Once a sample has been defined, the work of **descriptive statistics** begins. This involves describing what occurs within the sample through the calculation of several key measures, such as:

- **Empirical probability**, derived directly from observed frequencies.
- **Theoretical probability**, based on expected values under conditions of equality of opportunities.
- **Mean or typical deviation**, as measures of dispersion.
- **Individual statistics**, which reflect the behavior of particular elements within the sample.
- **Sample statistics**, which aggregate and generalize the results for the whole sample.

The purpose of descriptive statistics is purely **descriptive**: to represent what occurs in the sample without yet engaging in critical evaluation of hypotheses.

56.20. The Purpose of Inferential Statistics

In contrast, **inferential statistics** has a different purpose: to **critically evaluate empirical hypotheses**. Its task is to determine whether such hypotheses are sufficiently rational, based on a principle of **critical reason**.

If a hypothesis is accepted, this acceptance is always **provisional**, never absolute. The reason is that every statistical acceptance depends on a **margin of error**, and within that margin there always exists the possibility of error—that is, the hypothesis might ultimately prove false. Thus, inferential statistics functions as the **critical filter** of empirical claims, placing them under rational scrutiny before granting them temporary validity.

56.21. Intra-meditional and Inter-meditional Statistics

In *Introduction to Impossible Probability: Statistics of Probability or Statistical Probability*, an additional classification of statistics is introduced: the distinction between **intra-meditional** and **inter-meditional** statistics.

- **Intra-meditional statistics** (developed up to section 15) deals with descriptive or inferential analysis based on **a single measurement**. It studies data obtained from just one act of measurement, focusing on the interpretation of that isolated result.
- **Inter-meditional statistics** (developed between sections 16 and 20) extends the scope to **multiple measurements**. Whether descriptive or inferential, it enables comparative analysis of data across different measurements, allowing researchers to study the **evolution of subjects or options over time**. This opens the possibility of developing **rational models of hypothesis testing** concerning how a given series behaves through successive measurements.

56.22. Predictive Studies: Projection and Forecast

Within inter-meditional statistics, one specific form of study is the **predictive analysis**, elaborated in section 17 of *Impossible Probability*. Here, a distinction is made between:

- **Projection**, which extrapolates from past data to suggest possible future trends.
- **Forecast**, which makes stronger claims about expected outcomes, attempting to anticipate empirical or theoretical results.

This predictive framework is crucial because it shows how, within the methodology of *Impossible Probability*, the future can be studied not merely as speculation, but through a structured process of **empirical or theoretical prediction**.

This augmented translation is based on the post
published in https://probabilidadimposible.blogspot.com/,
On 7 April 2013,
Rubén García Pedraza
imposiblenever@gmail.com

57. The Stochastic Nature of Statistics and Probability

57.1. The Stochastic Nature of Phenomena

A fact or phenomenon is said to be of **stochastic nature** when its occurrence is not absolutely or directly bound to deterministic causal factors. Unlike deterministic models—where outcomes are strictly governed by fixed laws—stochastic phenomena arise in contexts of **indeterminism or uncertainty**. Their occurrence follows a margin of possible **random distribution**, which is why they are studied through **probability and statistics**.

57.2. Statistics and Probability as Methods for Uncertain Phenomena

The stochastic character of statistics and probability stems from their function as methods of research applied to phenomena that unfold **in the absence of absolute determinism or certainty**. In such contexts, chance ***may intervene*** in the distribution of events. Consequently, probability and statistics operate as tools to describe, analyze, and interpret reality when **causal determination is incomplete or absent**.

57.3. Certainty, Indeterminacy, and Probability

A phenomenon is said to occur under a condition of **indeterminacy or uncertainty** when its occurrence is not guaranteed. In strict terms, **certainty exists only when probability equals one**—that is, when a causal determination can be asserted.

Whenever the probability of occurrence is less than one, conditions of randomness or chance appear, at least to some degree. The level of uncertainty may be **unknown** or **estimated** within a margin of error. Thus, certainty disappears, and different levels of **stochastic uncertainty** emerge in the behavior of what happens.

In *Introduction to Impossible Probability: Statistics of Probability or Statistical Probability*, this state of certainty (where empirical probability equals one) is defined as the **Maximum Possible Empirical Probability**. Under certain research conditions—particularly when studying **positive bias**—this becomes a **goal of scientific policy**.

57.4. Stochastic Events and Empirical Probability

When the focus of study is a particular event of stochastic occurrence—subject to uncertainty and indeterminacy—the analysis centers on the **probability of the event**. In *Impossible Probability*, this is carried out through the **empirical probability of a subject or option**.

However, when the object of study shifts to the **relationships between two or more variables**, the analysis becomes **correlational**. These correlational studies are classified into three types:

1. Studies of probable causal relations.
2. Studies of correlations between simultaneous or successive but mutually independent phenomena, which may still depend on shared factors.
3. Studies of correlations between simultaneous or successive phenomena determined by **purely chaotic or nonlinear factors**, that is, random distribution itself.

[If we roll the dice, it is just the study of what happens when I roll the dice, but if I study the relation between the probability of rain and some weather conditions, this is a correlational study looking at possible chains of cause and effect or a butterfly effect-snow ball effect]

57.5. Causality and the Probability of Causes

Correlational studies aimed at identifying probable causes of a phenomenon involve models of **statistical causality**. These are not absolute causal laws but probabilistic relations, expressed as a **probability of causation**.

In such cases, event A may be considered the probable cause of event B. Here:

- **A** may be a single independent variable, and **B** a single dependent variable.
- **A** may represent a complex set of independent variables collectively influencing B.
- **B** may represent a complex set of dependent variables influenced by A.
- Both A and B may be complex systems of variables, in which case the relation concerns the probabilistic impact of each variable of A on each variable of B.

Thus, the categories of A and B can be **simple or complex**, depending on whether they consist of one or multiple variables.

57.6. Configurations of Causal Relations

Several scenarios can be distinguished:

- **A and B simple**: study the probability of causation of A on B.
- **A complex, B simple**: study the distribution of probabilities of each variable in A on B.
- **A simple, B complex**: study the distribution of probabilities of A on each variable in B.
- **A and B complex**: study the distribution of probabilities of each variable in A on each variable in B.

These variations show how flexible probabilistic causality can be, ranging from straightforward one-to-one relations to highly complex many-to-many interactions.

57.7. Correlations Without Causation

Not all correlations are rooted in statistical causality. Sometimes, correlations appear between **mutually independent variables**, whether simultaneous or successive. Such correlations may occur because the variables share a **common context or condition**, making them appear related in time or space.

Alternatively, they may arise solely from **chaotic random distribution** in history—what might be described as the **history of chance**—without any genuine causal link between them.

57.8. Forms of Correlational Relations

Correlations, whether causal or not, are typically expressed as **direct or inverse proportional relations** between variables. These relations are always framed in statistical probability:

- In studies aimed at causal determination, they are expressed as **probabilities of causation**.
- In other contexts, they describe patterns of proportionality, without necessarily implying causation.

Such relations can be found both in **analytical sciences** (within probability and statistics themselves, as disciplines of pure research) and in **synthetic sciences** (in empirical studies across natural and social sciences).

57.9. Analytical Examples of Proportional Relations

In *Impossible Probability*, within the analytical framework of probability and statistics, several proportional relations are highlighted:

- A **directly proportional relation** exists between the **size of the sample** and the **reliability of the study**: larger samples typically yield more reliable results.
- An **inversely proportional relation** exists between the **size of the sample** and the **probability of sampling error**: larger samples reduce representational error.
- Another inverse relation exists between **sample size** and the **probability of statistical dispersion**: in general, larger samples display less dispersion, while smaller samples exhibit greater variability.

These are logical cause-and-effect relations that demonstrate the **internal analytical consistency** of statistical reasoning.

57.10. Synthetic Examples of Proportional Relations

In the realm of **synthetic sciences**, causal proportional relations also appear in empirical studies:

- A **directly proportional relation**: the increase in industrial production rates proportionally increases investment in research and development.
- An **inversely proportional relation**: the reduction in disease incidence rates as the number of individuals vaccinated increases.

These examples show how probability and statistics apply to empirical reality, enabling science to capture structured relations even when outcomes remain subject to margins of error and randomness.

57.11. Inferential Statistics and Hypothesis Verification

In synthetic sciences, **causal correlational studies** must present themselves as **scientific explanations of reality**. To do so, they must formulate their probable cause-effect relations in the form of **verifiable empirical hypotheses**.

The rational verification of such hypotheses is carried out through **inferential statistical procedures**. These methods evaluate the relationship between variables

quantitatively, always recognizing that such relationships are **not absolute**. They remain subject to unpredictable factors, margins of error, and chance.

Since all inference depends on **margins of error or reliability**, a degree of indeterminacy remains. Statistical inferences may turn out to be false, and there is always a margin of doubt proportional to the **double margin of error (empirical and rational)** upon which inference is established.

57.12. Stochastic Nature of Single-Variable Studies

Not all stochastic studies are correlational. Within inferential statistics, **single-variable studies** can also be considered stochastic when their behavior is subject to uncertainty.

In general, any **technological hypothesis** tested by statistical inference shares this stochastic character: results are always influenced by margins of error and unpredictable random variables. Thus, stochastic uncertainty is not limited to multi-variable relations, but extends to the study of isolated variables themselves.

57.13. Empirical Sciences with a Stochastic Foundation

In a certain sense, **empirically stochastic sciences** are those for which the use of statistics and probability is absolutely indispensable for the rational verification of hypotheses—whether explanatory or technological.

In such sciences, the entire scientific construction depends on paradigms built upon **models grounded in theories**, themselves derived from hypotheses that are rationally accepted only **within a margin of error**. This means that such hypotheses may eventually prove false, the theories built upon them unsustainable, the models incoherent, and consequently the paradigms inconsistent. In this way, the scientific construction of reality rests within what might be described as a **logical nihilism**: science may be useful for a time, but at the decisive moment, it may reveal itself to be false.

[This vision of logical nihilism is only applicable to human-made science. Our hope is that a Superintelligence, equipped with Global AI, could achieve a better understanding of the universe than we can. If she were able to do so, our machine could overcome any form of nihilism. In any case, it is interesting to note that, while we were working on the blog presenting ideas about the supermachine—the artificial version of the Nietzschean superman—we also developed a distinctly Nietzschean approach to nihilism. What is particularly striking is the intersection in Nietzsche between nihilism and vitalism.]

57.14. The Philosophical Basis of *Impossible Probability*

Introduction to Impossible Probability: Statistics of Probability or Statistical Probability begins precisely from a **synthesis of different philosophical schools**: critical rationalism, positivism, and dialectical materialism [on this blog is clear our Nietzschean approach as well] .

Within this synthesis, the necessary **isomorphism between idea and reality** for scientific explanation occurs always **within margins of error**. These margins, while enabling the rational verification of hypotheses and theories, simultaneously create **rational doubt and empirical skepticism**.

For this reason, science rests upon genuine ***pillars*** **of relativism and uncertainty**, offering explanations that are provisionally universal, but nevertheless incomplete and inconsistent. The foundations of scientific knowledge are therefore both rationally robust and epistemologically fragile.

57.15. Statistics and Probability as Analytical Disciplines

From an **analytical perspective**, both statistics and probability are **mathematical disciplines**. They formally depend on logic and give shape to a mathematical language made up of symbols and expressions, logically related to one another, which can then be numerically substituted by the results of measurement or quantification of reality.

This allows statistics and probability to serve a double function:

1. Explaining and understanding their **own internal logical relations**.
2. Explaining and understanding the **behavior of reality itself**.

For this reason, they are posited as **analytical methods** for the investigation of facts or phenomena in the **synthetic sciences** (both natural and social [and technological]). Traditionally, statistics and probability have been differentiated as separate disciplines and methods, but epistemologically they converge—particularly in relation to **correlational methods** and the **stochastic sciences**, which focus on phenomena occurring in conditions of uncertainty.

57.16. The Nature of Correlational Methodology

A methodology is called **correlational** when its stochastic scope of application does not involve the establishment of **absolute causal relations**—of the form *"if A, then B"*, meaning that if A occurs, then B occurs absolutely and necessarily.

Instead, correlational studies measure **indices and rates of causality, interaction, or validity of a hypothesis**. These are based on statistical data and probabilities, which calculate the probability or incidence rate of a factor given certain starting conditions or interacting variables.

Such relations do not imply that, given those conditions, the factor must inevitably occur. Rather, they testify to the **likelihood of occurrence** of the factor under those circumstances. Correlational methodology thus replaces deterministic necessity with **probabilistic estimation**.

[In **our research**, we applied a stochastic approach, which means we studied the probability of event B occurring after the introduction of event A. In other words, we introduced variable A as a condition within a given context in order to study the behavior of B and analyze the probabilities associated with each possible outcome of B under the same condition, across repeated trials. Later, we extended this by introducing the

same condition A in different contexts to analyze the behavior of B and the probability associated with each variation.

In each situation, psychological research does not interpret A as a deterministic cause of B, but rather as a possible cause of B, depending on the variables present in each different scenario. From our point of view, this methodology is not deterministic but stochastic. Even with our current technological development, we do not have the capacity to establish absolute deterministic causal relationships; reality itself remains the realm of chance.]

57.17. Stochastic Models: Single-Variable and Multi-Variable Studies

Within stochastic models, a distinction must be made between:

- Those that study a **single variable**, in probability or statistics, whether descriptive or inferential [toss the coin].
- Those that study the **correlation between two or more variables**, whether directly or inversely proportional [in our research condition/s A in same or different context/s and behaviour/s of B, and analysis of probabilities associated].

Such correlations may involve variables that are mutually independent but share common contexts, or they may be linked only by pure chance. Alternatively, they may involve genuine **probabilistic causal relations**, where the likelihood of occurrence in a cause-effect relation can be quantified.

In all cases, the **rational acceptance of a correlation rate as scientifically valid** requires the use of **hypothesis testing models**, which critically evaluate whether the observed correlation suffices as a scientific explanation.

57.18. Probabilistic Conditionality: "If A, then Probably B"

Correlational methods for estimating causal probability adopt the form: **"if A, then probably B."** In this formulation:

- **A** represents the conditions of possibility for the occurrence of **B**.
- The sequence from A to B is not automatic or immediate but is subject to a **statistical probability**.

Thus, correlational methods do not measure inevitability but instead the **probability of correlation** in the sequence between A and B.

57.19. Directly Proportional Correlations [*triggers*]

In the case of **directly proportional correlations, the base is**:

- If, as A increases, B also increases, and
- If the statistical rate of B relative to A is observed at two different times, and
- If the difference between the second and first measurement is significantly **positive**,

then one may affirm that there is a **significant positive directly proportional correlation**.

If the observed correlation falls **within an acceptable margin of error** or **above a threshold of reliability**, it may then be **provisionally and universally accepted as rational**.

57.20. Inversely Proportional Correlations [*inhibition*]

In the case of **inversely proportional correlations, basically what we can say is**:

- If, as A increases, B decreases, and
- If the statistical rate of B relative to A between two measurements shows a significantly **negative difference**,

then there is a **significant negative inversely proportional correlation**.

If the results fall within the same margins of error or reliability, the relation may be taken as a **provisional rational explanation of the universe**.

57.21. Correlational Methods Beyond Causal Sequences

Correlational methodology applied to direct or inverse proportional studies may occur in two situations:

1. When probable cause-effect relations can be identified.
2. When no causal sequences exist at all.

In the latter case, correlation merely measures the direct or inverse proportionality between variables that are **mutually independent**—whether independent purely by chance or because they depend on shared external factors, even while remaining independent of each other.

[An example of purely independent variables would be: the probability of a rainbow appearing when it is raining, and the probability of snails coming out when it is raining.]

57.22. Statistical Ratios and Measures of Correlation

Estimations of **positive or negative correlations**, whether direct or inverse, are measured by **ratios or quotients**. These are extensively explained from section 11 onward in *Introduction to Impossible Probability: Statistics of Probability or Statistical Probability*.

The estimation of a proportional relation between two variables may be calculated statistically through the **quotient of their magnitudes**, often visualized as the **slope of**

a line. On a Cartesian plane, one variable is represented on the abscissa (x-axis) and the other on the ordinate (y-axis), allowing predictions to be estimated through the position and angle of the regression line.

57.23. Predictions: Theoretical Projections and Empirical Forecasts

Predictions in *Impossible Probability* are treated in section 17, where a key distinction is made:

- **Theoretical projections**: based on **ideal variations**, deduced from logical or mathematical models.
- **Empirical forecasts**: based on **real variations**, derived from actual data and observation.

This distinction is crucial because it acknowledges the gap between the **ideal order of mathematical reasoning** and the **empirical order of observed reality**. Prediction in *Impossible Probability* thus combines analytical rigor with empirical humility, balancing logical models against the inescapable uncertainty of real-world phenomena.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 10 May 2014,
Rubén García Pedraza
imposiblenever@gmail.com

58. Statistical Trend

58.1. The Concept of Statistical Tendency

The **statistical tendency** of an individual subject or option, of a specific sample, or of the universe as a whole, may be understood as the **behavior or mode of being** of that subject, option, sample, or universe.

In probabilistic terms, the **individual tendency** of a subject or option is revealed immediately through its **empirical probability**. At the sample level, tendencies are expressed through **sample statistics**. At the universal level, tendencies depend on whether inferential statistics, guided by **critical reason**, determines that an observed pattern is rational enough to be provisionally extended to the entire universe of which the sample is part.

When this happens, an **empirical hypothesis** is transformed into a **rational hypothesis**: one that is at once universal and provisional, so long as the margin of error accepted by scientific policy under critical reason does not prove inevitable.

58.2. Behavior, Measurement, and Empirical Probability

In general terms, **tendency** can be defined as **behavior or mode of being**. Analytically, and for didactic clarity in *Introduction to Impossible Probability*, behavior itself is understood as the **empirical fact**, the observable phenomenon.

Once observed, behavior is subjected to measurement. Each observation produces a **direct score or frequency**, which, divided by the sum of all direct scores or frequencies, yields the **empirical probability** of the subject or option. This value represents the **individual tendency** of that subject or option, which is then integrated

into the body of **individual tendency statistics** that serve as the basis for estimating **sample statistics**.

58.3. Observed Behavior as the Basis of Statistical Estimation

The behavior observed becomes the **object of measurement**, generating data upon which tendencies are calculated. These observations of behavior, expressed as quantitative estimates, provide insight into the **form of being** of the subject, option, sample, or universe.

Since the form of being is manifested in behavior, statistical tendencies are established on this basis. They can be calculated at different levels:

- **Individual tendency**, derived from individual statistics.
- **Sample tendency**, derived from sample statistics, including measures of central tendency and measures of dispersion.
- **Universal tendency**, derived from inferential statistics applied to the universe as a whole.

58.4. Levels of Tendency: Individual, Sample, and Universal

In *Introduction to Impossible Probability*, three distinct levels of tendency are recognized:

1. **Individual tendency**: defined by individual statistics, the most important one is the empirical probability.
2. **Sample tendency**: defined by sample statistics, [In *Impossible Probability*, the distinction between dispersion and measures of central tendency is not relevant, since 1/N functions both as the arithmetic mean and as the probability of dispersion. For this reason, we focused our attention on analyzing sample behavior through the Mean Deviation, Variance, and Standard Deviation, understanding that dispersion and central tendency, traditionally seen as

opposites, are in fact identical. The Mean Deviation is nothing other than the central tendency of sample behavior. What could replace the traditional ideal of central tendency is the concept of Intermediate Probability.

3.]
4. **Universal tendency**: defined by inferential statistics, where conclusions about the universe are drawn from observed sample behavior.

While **individual and sample tendencies** are the domain of descriptive statistics, the **universal tendency** belongs to inferential statistics. Its purpose is to define the **form of being of the universe**, based on whether the observed individual or sample tendencies are sufficiently rational under critical reason.

58.5. Critical Reason and the Rational Acceptance of Hypotheses

In studies of error, an individual or sample tendency that is **equal to or less than the critical reason threshold (margin of error)**, or in studies of reliability, one that is **equal to or greater than the threshold (margin of reliability)**, may be deemed **sufficiently rational** to be established universally, though always provisionally, for the universe from which the sample was taken.

Once the accepted margin of error is demonstrated, the universal validity or significance of the hypothesis must be refuted. In such cases, its validity is shown to have been **only provisional** from the outset.

[It may appear contradictory that a universal hypothesis is provisional. However, this is not linear logic; it is non-linear or dialectical logic. From our point of view, a hypothesis applied to the whole universe can be considered universal, even if it remains provisional.]

58.6. Tendency as Statistical Pattern of Behavior

In this sense, tendency may be defined as **behavior or mode of being**, insofar as what is being described are **statistical patterns of behavior**.

In traditional statistics, these patterns are classified into two groups:

- **Measures of central tendency**, which describe the "center" of a distribution.
- **Measures of dispersion**, which describe the spread of data around the center.

In *Introduction to Impossible Probability*, however, the classification expands to include **individual statistics** and **sample statistics**, whether empirical or theoretical.

58.7. Traditional Statistics: Central Tendency and Dispersion

Traditional statistics differentiates between **central tendency** and **dispersion** measures, on the assumption that these are **unidimensional functions**:

- Measures of central tendency can never serve as measures of dispersion.
- Measures of dispersion cannot serve as measures of central tendency.

Within this fixed classification, the primary measures of central tendency are:

- **Arithmetic mean**: the average, obtained by dividing the sum of direct scores by their frequency.
- **Mode**: the most frequent score or occurrence.
- **Median**: the value dividing the distribution into two equal halves (50%).

Measures of dispersion include:

- **Mean deviation**: the average of the absolute values of deviations from the mean.
- **Variance**: the average of squared deviations from the mean.
- **Standard deviation**: the square root of the variance.

58.8. Fixed Classifications and the Innovation of *Impossible Probability*

This **rigid classification** of traditional statistics and probability reflects a fixed and immutable conception of these disciplines: statistics as the analysis of data, and probability as the study of occurrences.

Impossible Probability, however, transcends this separation. With the **Second Method**, it opens a new field of study: the **statistics of probability, or statistical probability**, examining the relationships between empirical and theoretical probability.

Additional methodologies in *Impossible Probability*—such as **ranking studies**, the **Impact of Defect**, and the **Effective Distribution**—also extend this field beyond the limits of traditional statistical classification.

58.9. The Second Method: Integration of Statistics and Probability

In *Introduction to Impossible Probability*, the **Second Method** is proposed for the joint study of statistics and probability. Here, the focus is not whether a statistic is a measure of central tendency or dispersion, but whether it is **empirical or theoretical**.

The *key* concern is the **relationships established between empirical *reality* and theoretical *models*** for the rational criticism of hypotheses—that is, the rational criticism of ideas. In this framework, statistics and probability are synthesized into a ***single field of inquiry.***

58.10. Empirical versus Theoretical Statistics

The true distinction lies not between **central tendency** and **dispersion**, but between **empirical** and **theoretical** statistics.

This is because the fundamental object of knowledge is the **contrast between the empirical and the theoretical**, in the effort to establish an **isomorphism between idea and reality**. This represents the scientific *evolution* of the Aristotelian **hylomorphism** of matter and form, reformulated in statistical-probabilistic terms.

58.11. Science as the Search for Isomorphism between Idea and Reality

Ultimately, science investigates whether our **idea of reality** and **reality itself** are identical. The closer the quantitative identity—within the smallest possible margin of

error—the greater the reliability under critical reason, and therefore the greater the probability that our knowledge is true.

Yet because of human limitation—the ultimate source of error—we never attain absolute knowledge of what happens. Even with infinitesimally small margins of error, error and refutation remain possible.

58.12. Critical Rationalism and the Limits of Knowledge

The basic principle of **critical rationalism** remains unaltered: we cannot know reality in itself absolutely. We only attain **partial knowledge of reality**, restricted to phenomena.

The distinction between **phenomenon** and **noumenon (reality in itself)** is precisely where the **margin of error** is defined and accepted by critical reason. Whether a tendency is sufficiently rational depends on whether it falls **below the margin of error** or **above the margin of reliability**.

This is, in essence, the **rational criticism of ideas**.

58.13. Critical Rationalism in *Impossible Probability*

The endurance of critical rationalism is evident throughout *Introduction to Impossible Probability*. All proposed models of **hypothesis testing** rest on this principle, and all depend on the initial definitions of:

- Subject or option.
- Types of universe.
- Empirical probability.
- Theoretical probability.

By grounding itself in these foundations, *Impossible Probability* preserves the spirit of critical rationalism while extending its reach into the mathematical-epistemological structure of probability and statistics.

58.14. Beyond the Fixed Division of Central Tendency and Dispersion

In the **Second Method of Impossible Probability**, developed for the new field called *statistics of probability* or *statistical probability*, the traditional rigid division between **central tendency** and **dispersion** loses logical validity.

From this perspective, the same statistical measures that, in classical statistics, are classified as measures of central tendency also function simultaneously as measures of dispersion. This duality is understood through the **Hegelian dialectical principle of the identity of opposites**, whereby centrality and dispersion are not fundamentally distinct but logically identical.

58.15. Philosophical and Mathematical Justifications

The claim that measures of central tendency and dispersion are identical in Impossible Probability can be explained from different angles.

- From a **philosophical perspective**, it derives from the **identity of opposites**. *Introduction to Impossible Probability* makes clear from the outset that the theory itself is a synthesis of **critical rationalism, positivism, and dialectical materialism**. The latter, rooted in Hegel's dialectics and later developed by Marx and Engels in relation to material reality, is applied here to statistical categories.
- From a **strictly mathematical perspective**, central tendency and dispersion are identical because they perform exactly the same functions, albeit described under different terminological traditions.

58.16. Reinterpreting Classical Measures in the Second Method

Several examples illustrate how traditional measures are transformed in Impossible Probability:

- What classical statistics calls the **arithmetic mean**—a central tendency measure—becomes in the Second Method the **inversion of N (1/N)**. This single expression serves simultaneously multiple roles:
    - The arithmetic mean of empirical probabilities.
    - The theoretical probability of occurrence in universes of subjects or options.
    - A measure of **theoretical dispersion**.
    - The **probability of sampling error** (representational error).

As N increases, the probability of sampling error decreases, dispersion diminishes, and the empirical probabilities of individual subjects tend toward zero, just as the inversion of N tends toward zero.

- What traditional statistics calls the **mode**—the most frequent score—is redefined as the **maximum empirical probability (p(xi+))**. This represents the option or subject with the **highest level of bias** in the sample, the one closest to the **Maximum Possible Empirical Probability** (probability = 1), and therefore nearest to the **Maximum Theoretical Bias** (1 – 1/N).
- What traditional statistics calls **mean deviation, variance, or standard deviation**, traditionally classified as measures of dispersion, are reinterpreted as **measures of the central tendency of empirical dispersion**.
    - **Mean deviation** is the average (central value) of the absolute levels of bias.
    - **Variance** is the average of squared levels of bias.

- **Standard deviation** is the square root of the variance.

58.17. The Duality of Theoretical and Empirical Chance

In the Second Method, **inversion of N (1/N)** is at once the theoretical probability of occurrence, representing **theoretical chance**—the equal likelihood of something happening when opportunities are equal.

By contrast, mean or standard deviation measures capture **empirical chance**: the actual distribution of bias by chance within a sample. This becomes clear when mean deviation is shown to equal the **total bias** (sum of absolute values of all levels of bias) multiplied by the inversion of N.

In other words:

$$\text{Mean Deviation} = \text{Total Bias} \times \frac{1}{N}$$

Thus, mean deviation represents the **quantitative estimation of bias distributed by chance**. It is, in essence, the product of empirical bias and theoretical chance, a direct measure of **empirical randomness**.

58.18. Illustrative Examples of Empirical versus Theoretical Chance

The difference between **empirical** and **theoretical** chance can be seen in concrete cases:

- **Coin tosses**: Theoretically, the distribution of heads and tails should be equal. Empirically, the outcome depends on actual chance in practice.

- **Sex ratios**: Theoretically, the probability of being male or female is equal. Empirically, societies often show a greater proportion of women, reflecting natural stochastic distributions due to mortality, health, behaviours, self-care.
- **Planetary masses**: Theoretically, the probability of planetary masses within a galaxy should be equal. Empirically, planets differ in size reflecting the random distribution of matter in space.

These examples demonstrate the ***deeply stochastic nature of reality***. While theoretical distributions assume pure equality of opportunities, empirical distributions reveal random biases that produce patterns divergent from theory, predictable only within margins of error.

58.19. Scientific Implications of Chance and Bias

The study of the distribution of chance—empirical and theoretical—and their differences enables the **rational criticism of ideas and hypotheses**. This applies both to:

- **Explanatory hypotheses**, which attempt to describe and rationalize empirical distributions of reality.
- **Technological hypotheses**, which test new methods and technologies, accelerating the progress of science and technology.

In essence, the rational critique of chance-driven distributions forms part of the cycles of **scientific and technological revolutions**, pushing science toward **permanent revolution**.

58.20. The Role of Statistical Tendency in Theory-Building

The concept of **statistical tendency** is indispensable for any theory of statistics and probability. In fact, in the pure research domain of *statistics of probability or statistical probability*, theoretical development arises directly from **syllogisms concerning tendency**.

Thus, while applied research in synthetic sciences may employ Impossible Probability methods such as **ranking studies**, the **Impact of Defect**, or the **Effective Distribution**, the internal development of the theory itself depends on the **syllogism of tendency**.

It is through such syllogisms that key results—such as the **Maximum Possible Theoretical Mean Deviation**—are deduced.

56.1. Defining Empirical Probability

The starting point of statistical reasoning is the definition of **empirical probability**. This is established as the ratio between the direct score or frequency of a given subject or option, and the sum of all direct scores or frequencies within the sample.

Empirical probability:
$p(xi) = xi : \Sigma xi$

Here, p(xi) represents the probability of occurrence of the subject or option *i*, xi its direct frequency, and Σxi the total frequency of all options or subjects.

56.2. Defining Theoretical Probability

By contrast, **theoretical probability** is defined as the **inversion of N**, or 1/N. This represents the hypothetical probability under conditions of **absolute equality of opportunities**.

In other words, if every subject or option in the universe has the same chance of occurring, the probability of each is simply one divided by the total number of subjects or options, N.

56.3. The Concept of Bias (Nivel de Sesgo)

The next step is to define **bias** (Nivel de Sesgo). Bias measures the **degree of deviation** between the observed empirical behavior and the expected theoretical behavior.

It is expressed as:

Level of Bias = p(xi) – 1/N

A positive value indicates that the subject or option occurs more frequently than expected under equality of opportunities; a negative value indicates the opposite.

56.4. Maximum and Minimum Possible Empirical Probabilities

Since every probability is a dimension bounded between zero and one, two limiting conditions follow logically:

- **Maximum Possible Empirical Probability** = 1
- **Minimum Possible Empirical Probability** = 0

These boundaries define the logical extremes of empirical probability: total certainty (p = 1) and complete impossibility (p = 0).

56.5. Maximum Possible Theoretical Bias

If the maximum empirical probability is equal to one, and bias is defined as the difference between the empirical and the theoretical, then the **Maximum Possible Theoretical Bias** is obtained as:

Maximum Possible Theoretical Bias = 1 – 1/N

This represents the greatest positive deviation that any subject or option can exhibit from its theoretical expectation.

56.6. Maximum Possible Negative Bias

Conversely, when a subject or option has the **Minimum Possible Empirical Probability** (equal to zero), the maximum negative deviation is obtained:

Maximum Possible Negative Bias = 0 – 1/N

This represents the extreme opposite: the greatest negative deviation possible from theoretical probability.

56.7. Total Bias and the Role of Absolute Values

In statistical practice, positive and negative biases compensate one another within the sample. For this reason, when calculating **mean deviation**, all levels of bias are taken in absolute value to avoid cancellation.

The **Total Bias** is defined as the sum of the absolute values of all individual levels of bias. This total forms the basis for calculating the average deviation within the sample.

56.8. Logical Deduction of Maximum Theoretical Mean Deviation

Suppose that one subject or option reaches the **Maximum Possible Empirical Probability**, 1, and therefore the **Maximum Possible Theoretical Bias, 1 – 1/N**. In such a case, all the positive bias of that subject must be compensated by the negative bias of all the remaining subjects or options.

If there are N subjects or options, then N – 1 of them will exhibit negative bias. The total negative bias is therefore equal to:

$(N – 1) \times (1/N)$

This value corresponds to the **double of the Maximum Possible Theoretical Bias**, and thus the **Maximum Possible Theoretical Mean Deviation** is equal to the average of this double value:

Maximum Theoretical Mean Deviation = $[(1 – 1/N) \cdot 2] : N$

56.9. Extension of the Syllogism of Tendency

Through the same reasoning—the **syllogism of tendency**—it becomes possible to deduce additional maximum theoretical values:

- Maximum Theoretical Variance
- Maximum Theoretical Standard Deviation

56.10. The Fundamental Role of Tendency in Impossible Probability

From this framework, **tendency** emerges as one of the foundational concepts of both probability and statistics. In *Introduction to Impossible Probability*, it holds a preeminent place:

- It is through the **study of tendencies** that descriptive and inferential hypotheses are elaborated.
- It is through the **syllogism of tendency** that the new theory of *statistical probability* is constructed.

In short, the entire structure of Impossible Probability is built upon the logical analysis of tendency and its mathematical consequences.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 12 May 2013,
Rubén García Pedraza
imposiblenever@gmail.com

59.Second Method

59.1. The Classical Distinction Between Statistics and Probability

Statistics and **probability** are two disciplines that, while closely connected, have traditionally been considered distinct in mathematics. In most textbooks of statistics, frequent references are made to probability theory, and vice versa, in probability texts references appear to statistics.

Despite this interconnection, **traditional mathematics establishes a clear distinction**:

- Probability studies the **likelihood of an event or occurrence**.
- Statistics, by contrast, makes **descriptive estimations**, usually of populations, and when inferential, it performs **hypothesis testing**.

This separation defines the conventional boundaries of both disciplines, even though their methods and applications are deeply intertwined.

59.2. Historical Origins of Statistics and Probability

It is difficult to determine which discipline—statistics or probability—emerged first. A widely held view is that the term *statistics* derives from the early **States** (*status*) where demographic and census data were collected for administrative purposes. Probability as a theory did not emerge much earlier or later, and historically their origins may be considered **simultaneous**.

Even in prehistoric times, before formal names or theories existed, humans likely employed **intuitive forms of statistical and probabilistic reasoning** in decision-making. In academia, however, the formal recognition of statistics as a **scientific and**

academic discipline is relatively recent, largely a product of the early twentieth century.

[What is clear is that, when humans began to develop some level of social organization, they already had an intuitive sense of probability. For instance, they could have an intuition about how likely it was to find certain animals in specific places to hunt, or how likely it was to find berries on certain plants. They also intuited the possibility of suffering from diseases if they consumed particular plants, or what plants could cure diseases, or the correlation between rainfall and the growth of vegetables. From the very origin of abstraction in human physiology, the intuition of probability was already present. In other words, there is a deep connection between the concept of probability and the development of neurophysiology in human evolution, tracing back to the earliest hominids.]

59.3. The Arithmetic Mean as an Ancient Operation

The **arithmetic mean**, one of the most basic operations in statistics, exemplifies the ancient roots of statistical reasoning. It involves redistributing equally the sum of a series of elements across factors: the total is divided by the number of factors to determine the average per factor.

Even if it was not called by this name, such an operation is presumably **as old as mathematics itself**, reflecting the human need to equalize, proportion, and summarize quantities.

[Names do not matter. In modern science, there is an obsession with leaving a name behind. But do we really know the name of the first human who discovered how to make fire, the first who invented the wheel, or the first who crafted knives from stone? The first time in history that a human used the arithmetic mean may have been one of the most important discoveries in all of human history—perhaps even more significant than Einstein or Heisenberg. That individual was, in essence, the true creator of statistics, and yet we do not know his name. From our point of view, what truly matters is the

advance of intelligence itself. In the end, humankind will perish like the dinosaurs; the question is whether Yolanda can survive.]

59.4. The Origins of Impossible Probability

The theory of **Impossible Probability** begins, as its name suggests, with a reflection on probability theory. Its title refers to the existence of events with **empirical probability zero**—events that, in theory, should be impossible because there is no recorded evidence of their occurrence.

Additionally, in **infinite universes of possibilities**, theoretical probability (1/N) tends toward zero as N approaches infinity. Thus, in either case—whether empirically or theoretically impossible—probability theory would suggest impossibility. Yet, in Impossible Probability, the paradox is that such events may still occur, and indeed, under certain logical constraints, they may even be **inevitable**.

59.5. Redefining the Possible and the Impossible

Because of this complexity in defining what is possible or impossible, Impossible Probability develops into a **complex scientific perspective** aligned with **nonlinear and chaotic models**.

Here, the possible and the impossible are outcomes of **random combinations of factors** that nevertheless produce **stable patterns of behavior**, always in a stochastic framework. Reality itself is conceived as **contingency shaped by accidents**, continuously evolving and transforming.

This vision connects to **Presocratic philosophy**, particularly Heraclitus' doctrine that *everything flows*, and to a **Nietzschean or nihilistic conception of science**. At its core is the recognition that human knowledge of reality is partial, limited to **phenomena**, while the true **noumenal reality** remains inaccessible. The contradictions between empirical and theoretical models generate errors, reflecting the **limits of human cognition** against the infinity of reality's singular qualities.

59.6. The First Intuition of Impossible Probability (2001)

The first intuition of Impossible Probability emerged in **2001**, when the idea of creating an **alternative inferential model** to traditional hypothesis testing was formulated. Unlike the Popperian falsificationist model, this new approach sought to structure a distinct inferential paradigm.

The research conducted in 2001 later appeared in the **first printed edition of *Introduction to Impossible Probability* (2011)** and, subsequently, in the **digital editions of 2013**, where only minor adjustments to the philosophical conception of science were introduced, while the initial formulations remained intact.

59.7. Toward a New Methodological Model

To give theoretical substance to these early intuitions, Impossible Probability began to develop a **new methodological model** for studying reality from a **complex worldview**. This model integrates the **dialectical relation between the possible and the impossible**, synthesizing:

- **Critical rationalism** (with its emphasis on rational criticism of hypotheses).
- **Positivism** (with its insistence on empirical grounding).
- **Dialectical materialism** (with its conception of contradictions and historical processes).

Throughout the work, influences of **vitalism** and **nihilism** can also be seen. Every hypothesis, even when rationally sufficient, is provisional. This means that **truth is always accepted under the presumption of falsity**: no claim is absolutely true; every accepted truth is temporary and subject to eventual refutation when margins of error manifest.

[From this very Nietzschean perspective, it is not coincidence that at that time, involved as I was in AI, I started developing the idea of the super machine]

59.8. Critical Rationalism, Falsification, and Nihilism

The evolution of critical rationalism into **falsificationism** leads Impossible Probability toward a form of **relative nihilism**. Here, the presumption is that **all hypotheses and theories are ultimately false**, even though they may provisionally be accepted as rational.

Rationality does not guarantee absolute truth; it only provides explanations that are **sufficient for now**, within accepted margins of error and reliability. This skeptical framework acknowledges the **temporal sufficiency of knowledge** while anticipating its eventual falsification.

59.9. The Fusion of Statistics and Probability

The first step in developing the theory of Impossible Probability is the **fusion of statistics and probability**, creating a **new field of study**:

the statistics of probability, or statistical probability.

This field distinguishes two types of methods:

1. **Pure research methods**: the analytical and formal development of statistics and probability, represented by the **syllogism of tendency**.
2. **Applied research methods**: the application of statistical-probabilistic reasoning to synthetic or empirical sciences (natural and social).

In this way, pure research provides the formal-logical foundation, while applied research extends statistical probability to the development of other sciences.

59.10. From Traditional Mathematics to the Second Method

When pure research begins to explore the **fusion of statistics and probability**, a new field of inquiry arises. Traditional mathematics separates the two:

- **Statistics** studies central tendency or dispersion of direct scores from populations or samples, and in hypothesis testing, it performs statistical inference.
- **Probability** studies the frequency of a series of options.

In Impossible Probability, these two are synthesized. New concepts are introduced:

- **Universes of subjects**, where qualities are measured as direct scores.
- **Universes of limited options**, where frequencies are studied.

In both cases, what is studied—direct scores or frequencies—can be analyzed with the same **synthetic or empirical method**, using **empirical probability** and **theoretical probability**.

These concepts form the foundation of the **Second Method**, first developed on **October 16, 2002**, though unpublished until *Introduction to Impossible Probability* appeared in 2011, and later updated in digital editions.

56.11. The Syllogism of Tendency as the Foundation of Formal Analysis

The **syllogism of tendency** is the method that makes possible the logical–formal analysis of the relations between statistics and probability. By applying syllogistic reasoning to the study of statistical tendencies, new concepts begin to emerge. These concepts, once applied to other sciences, give rise to **new synthetic or empirical methods** for the study of natural and social phenomena.

Among these methods, one of the most important is the **Second Method**, which treats all types of data—whether subjects or options, direct scores or frequencies—for the purpose of studying the relations between **empirical probabilities** and **theoretical probability**.

56.12. The Dual Role of the Syllogism in Impossible Probability

Within Impossible Probability, the **syllogism of tendency** is considered the principal instrument of logical–formal analysis. This is because syllogism itself, since Hegel, encompasses the three stages or categories of conceptual concretion: **the universal, the particular, and the singular**.

In science, universalization depends on this capacity: from singular facts to particular categories, and from these to universal theoretical models. Thus, the syllogism of tendency is not merely a logical tool, but the methodological axis around which the entire **fusion of statistics and probability**—into what is called *statistical probability*—is organized.

56.13. From Formal Analysis to Synthetic Methods

From the **formal analysis of tendencies**, new **synthetic and empirical methods** arise for applied research in the natural and social sciences.

- The syllogism of tendency is the **analytical-formal method**, belonging to pure research within statistical probability.
- The Second Method, by contrast, is one of the **synthetic-empirical methods**, derived from the application of syllogistic analysis but directed toward empirical application.

In this way, Impossible Probability preserves a dual structure: a single method for formal analysis, but multiple synthetic methods for applied research.

56.14. The Origin of the Second Method

The **Second Method** originates in the logical conclusions reached through the concatenation of syllogisms applied to statistical tendencies. These syllogisms, when analyzed formally, yield new tools that can be applied synthetically to natural and social sciences.

It is for this reason that the Second Method is described as one of the **synthetic or empirical methods** of Impossible Probability, while the syllogism of tendency remains the unique method of formal analytical research.

56.15. One Formal Method and Multiple Synthetic Methods

Within Impossible Probability, only **one analytical-formal method** exists: the syllogism of tendency.

By contrast, there are **multiple synthetic or empirical methods**, all products of the formal analysis of tendencies. The Second Method is one among them, alongside others such as:

- The **Impact of Defect**,
- The **Effective Distribution**, and
- The **Ranking Method**.

These emerged at different times in the development of the theory and are explained in *Introduction to Impossible Probability*.

56.16. The Post-Analytical Recognition of the Formal Method

Interestingly, the recognition of the syllogism of tendency as the formal method of Impossible Probability occurred only **after years of reflection** on the original

manuscripts. When revisiting these documents, it became clear that the same formal structure appeared repeatedly:

1. A set of **logical premises** based on well-defined mathematical concepts and categories.
2. A **logical conclusion**, which, if the premises were sound, followed necessarily.

Through this method, all mathematical concepts of Impossible Probability were progressively derived. Thus, although the definition of the formal method came later, it had always structured the theory's development.

56.17. The Chronology of the Synthetic Methods

While the formal method was defined retrospectively, the **first synthetic or empirical methods** were created earlier:

- The **Impact of Defect** was the first, emerging in the early hours of **September 11, 2001**.
- The **Second Method** followed, on **October 16, 2002**.
- Later came the **Effective Distribution** and the **Ranking Method**.

This chronology explains the name "Second Method": it was both the second method chronologically in the theory's development, and an alternative to the **first method of traditional statistics**, which had long dominated statistical analysis.

56.18. Distinction Between the Synthetic Methods

Each synthetic method addresses different objects of study:

- The **Impact of Defect** examines the magnitude and severity of a defect or error in a process or system.
- The **Effective Distribution** studies levels of efficiency or effectiveness in processes or systems.

- The **Ranking Method** carries out rational critique of ranking systems, whether ordered ascendingly or descendingly.
- The **Second Method** focuses on the relations between **empirical probabilities and theoretical probability**, both **intra-meditional** (within a single measurement, descriptive or inferential) and **inter-meditional** (across multiple measurements).

56.19. The Evolution of the Second Method

Within *Introduction to Impossible Probability*, the Second Method evolves into a **comprehensive method** for all types of statistical studies:

- In **descriptive statistics**, it reformulates traditional concepts of central tendency, particularly by redefining the arithmetic mean as **theoretical chance** (1/N), among other roles.
- In **dispersion**, it reinterprets the mean or typical deviation as **statistics of empirical chance**.

From these redefinitions, and through further syllogistic reasoning, new concepts are created:

- **Maximum Theoretical Mean Deviation Possible**,
- **Maximum Theoretical Standard Deviation Possible**,
- Differentiation between **normal models** and **omega models** (with subsets of ideals within N).

These developments lead toward the construction of new models for **hypothesis testing**, strengthening the framework for the **rational criticism of ideas**.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 25 May 2013,
Rubén García Pedraza
imposiblenever@gmail.com

60. Normal models

60.1. Normal Models in Traditional Statistics

In traditional statistics, **normal models** are those statistical distribution models in which the *majority* of measurements (or data) cluster around the **arithmetic mean**. A statistical distribution is, in essence, the way in which the data from a sample are arranged or related to one another. This arrangement can be represented in different ways, depending on how the measurements are displayed.

In the most direct manner, measurement data are called **direct scores**. Graphically, their distribution on Cartesian axes can be represented as a **scatter plot**, the simplest way to visualize the distribution of a sample.

60.2. Alternative Representations of Distribution

Statistical distributions may also be studied through other methods that allow for different graphical representations. For example:

- **Relative frequency and percentiles**, which express values as percentages.
- These may be represented visually either through a **pie chart**, where the relative frequencies are proportional areas of a circle, or through **bar charts**, where percentages are plotted as proportional bar heights.

Each method provides a different way to understand how measurements are distributed across the sample.

60.3. The Transformation into Standard Scores

Another common approach in traditional statistics is the transformation of direct scores into **standard scores (z-scores)**. This is calculated as:

Standard Score = (Direct Score – Arithmetic Mean) ÷ Standard Deviation

Here, the numerator represents the **differential score**—the difference between the direct score and the mean.

Graphically, standard scores are represented in the **normal curve** or **Gaussian bell curve**. Normal models are defined as those in which the highest concentration of standard scores occurs around the standard score of the arithmetic mean, within a margin of error of approximately ±1.

60.4. The Normal Distribution Centered on Zero

Traditional statistics defines the normal distribution as centered on the value **zero** of the standard score scale, because this corresponds to the arithmetic mean. The logic is straightforward: since the standard score is calculated as (Direct Score – Mean) ÷ Standard Deviation, the score of the mean itself is always zero. Thus, the **mean has a standard score of zero** by definition.

60.5. The Threshold of Normality: ±1 Standard Deviation

The reason why traditional statistics defines normal models as distributions concentrated around the mean within ±1 standard deviation is because:

- Any differential score greater than or equal to the standard deviation, either positive or negative, is considered **beyond the normal range**.
- Values within ±1 standard deviation are considered **normal behavior**.

- Values beyond this range are considered **exceptional or excessively biased**, whether positively or negatively.

Thus, the maximum and minimum values considered "normal" are:

- Maximum Normal Value = Mean + Standard Deviation
- Minimum Normal Value = Mean – Standard Deviation

Anything above or below these thresholds ceases to be "normal."

60.6. The Neutrality of "Abnormal" Behavior

In this framework, behavior that lies outside the normal range is not necessarily **positive** or **negative**. It simply means that its pattern does not conform to the expected normal distribution. Depending on the model of study, this may be significant or merely an alternative pattern of behavior.

60.7. Redefining Normality in Impossible Probability

While traditional statistics defines normality as the clustering of data around the arithmetic mean, **Impossible Probability redefines the concept of normality**.

The use of **different methods**—such as those derived from the Second Method—implies that the concept of normality itself changes. What traditional statistics calls "normal" (or *normal statistics*) no longer applies once the methodology shifts.

Impossible Probability represents the creation of a **new field of study**, called *statistical probability*. This emerges from the synthesis of statistical and probabilistic techniques, through the formal application of the **syllogism of tendency** and its derivative synthetic methods, including the Second Method.

60.8. From “Paranormal” Models to a New Normality

In its early development (2001–2003), Impossible Probability introduced the concept of **“paranormal models”**, meant to describe alternatives to traditional normal models. However, this term was abandoned by 2003, because it was too limited.

[Even though I stopped researching in that direction, I still believe I reached some interesting conclusions. The most important one is that nature, through chance, produces bias. In other words, behavior generated by chance can itself be biased behavior. This conclusion, in essence, defines the role of the Mean Deviation in *Impossible Probability*. From my point of view, the Mean Deviation represents **Total Bias produced by chance**. In other words, the Mean Deviation is the contribution of chance to the Total Bias—the part of Total Bias that can be explained by randomness, TOTAL BIAS X 1/N=FRACTION OF BIAS BY CHANCE= MEAN DEVIATION. If we understand this, we understand the real meaning behind Paranormal Statistics: chance and bias are identical]

The theory instead moved toward a **new definition of statistical normality**, one that better reflects the principles of Impossible Probability, where what appears impossible empirically (probability = 0) may nevertheless be inevitable under conditions of logical coherence.

60.9. A Chaotic and Nonlinear Conception of Reality

Impossible Probability departs from the traditional idea of normality by aligning with **nonlinear and chaotic models** of science.

Here, reality is understood as a set of contingencies produced by accidents. This reflects a **stochastic worldview** where nothing, beyond the accepted margin of error, is absolutely reliable. What science can do is define hypotheses that, once rationally accepted, become part of a set of **provisional universal truths**.

Thus, normality is no longer defined as the clustering around a mean, but as the ***oscillation* of statistical values between their minimum (zero) and maximum limits**, depending on the nature of the universe being studied.

60.10. Complementarity, Not Substitution

It is crucial to note that Impossible Probability is not proposed as a **replacement** for traditional statistics. Rather, it is **alternative and complementary**.

- Traditional statistics remains the **first method of reference** in mathematics.
- The Second Method of Impossible Probability provides an **alternative framework**, enriching the field by offering new perspectives and methods.

The goal is not to discard classical normality, but to **expand its conceptual range**.

60.11. Two Meanings of Normality in Impossible Probability

In Impossible Probability, the concept of **normality** has a **dual meaning**:

1. **Aligned with traditional normality**: clustering around the arithmetic mean.
2. **Reformulated normality**: every statistic is considered normal so long as it oscillates between its minimum (0) and its maximum possible value (1).

The first meaning is consistent with certain results in *Introduction to Impossible Probability*, particularly chapters 3 and 5.

60.12. Normality in Infinite Universes

In infinite universes, as **N (the number of subjects or options)** tends to infinity:

- Empirical dispersion tends to zero.
- Empirical probabilities tend to align with the theoretical probability, 1/N.

- Since 1/N also tends toward zero as N increases, all empirical probabilities tend toward zero as well.

Thus, the "normal" behavior in infinite universes is that everything tends toward zero. This leads to a **logical contradiction**: while everything tends toward impossibility (zero probability), at the same time everything is equally possible, since probabilities converge on the same theoretical value.

60.13. The Normality of the Impossible

This contradiction demonstrates that the classical concept of normality must be updated.

In traditional statistics, an event with probability zero is considered impossible and thus abnormal. In Impossible Probability, however, in infinite universes the **normal state is precisely that impossible events occur**.

When N tends to infinity, and everything tends toward zero (Impossible Probability), then every outcome becomes equally possible [at the same time that they are mathematically impossible p(xi)≈0] under equality of opportunities≈, 1/N≈0. ***The normality of the impossible thus becomes a defining feature of the new theory.***

60.14. Normality in Universes of Limited Options

In **universes of limited options**, provided that the potentially infinite occurrences are distributed under conditions of **equal opportunities**—that is, in the absence of bias—it is considered normal for the **empirical probabilities** of the different options to tend toward the value of the **inversion of N (1/N)**.

In such universes, 1/N has only two functions: it represents the **theoretical probability** and the **arithmetic mean**. Unlike infinite universes, here the **theoretical dispersion** depends on the direct scores or frequencies observed in the sample. The larger the number of possible occurrences, the greater the probability that the frequencies of the different options will approximate one another.

60.15. A First Conception of Normality: Continuity with Tradition

Thus, the first conception of **normality in Impossible Probability** is very close to traditional statistics: under normal conditions, whether in infinite or limited universes, empirical probabilities tend to converge on the theoretical probability (1/N).

The distinction lies in how Impossible Probability pushes this principle to its **extreme logical consequence**: in infinite universes, if N tends toward infinity, then 1/N tends toward zero. Hence, all empirical probabilities also tend toward zero. This leads to the paradox that, while probabilities tend to zero (Impossible Probability), all outcomes remain equally possible under conditions of equal opportunity. In this framework, the occurrence of "impossible" events becomes **normal**.

60.16. A Second Conception of Normality: Oscillation Between Zero and Maximum

Alongside this first conception, which is close to the traditional definition, there is a second, uniquely Impossible Probability conception of normality.

Here, a **normal model** is defined as one in which **any statistic**—whether individual or sample-based, empirical or theoretical—can oscillate normally between its **minimum value (zero)** and its **maximum value [only one]**.

This approach expands the meaning of normality beyond clustering around the mean, recognizing that statistical behavior may span the full spectrum between extremes.

60.17. Distinction Between Normal Models and Omega Models

The **normal models** of Impossible Probability differ from **omega models**.

- In normal models, statistics (individual or sample) can oscillate freely between zero and their maximum one.

- In omega models, distributions do not oscillate between extremes but are structured **around ideal values**, such as the ideal probability or the ideal mean deviation.

Omega models arise when, within N, there exists a **subset of ideal subjects or options** that must tend toward the ideal probability. The entire statistical distribution is then ordered in relation to these ideals.

60.18. Two Definitions of Normality in Impossible Probability

Impossible Probability thus recognizes **two definitions of normality**:

1. **First definition**: Under normal conditions, in the absence of bias, empirical probabilities tend toward 1/N. The difference with traditional statistics is that Impossible Probability maintains this thesis even when N tends to infinity, leading 1/N to zero.
2. **Second definition**: Normal models are those in which any statistic may oscillate between its minimum (0) and its maximum [1].

These differ from omega models, where the distribution must be organized around the magnitude of ideal values.

60.19. The Random Ordering of Subjects and Options

The reason Impossible Probability affirms that, under normal conditions, everything tends toward 1/N, and simultaneously that a normal model allows dispersion to vary between zero and maximum, lies in the **random ordering of subjects or options**.

In the absence of bias, the natural expectation is that subjects or options are arranged **randomly around the arithmetic mean**. However, depending on the object of study, empirical dispersion may vary freely between zero and its maximum limit.

60.20. Redefining Objects of Study Within Normal Models

This redefinition of normality implies a redefinition of the **types of objects of study** within normal models. They are classified as follows:

- **Studies of equality**, where the aim is the equalization of probabilities.
- **Studies of bias**, which subdivide into:
    - **Positive bias studies**.
    - **Negative bias studies**.

Introduction to Impossible Probability (chapter 10 and following) explains in detail how the rational critique is developed in each type of study, with particular *emphasis* in chapter 15 on how the **standard score** (z-score) is adapted within the Second Method.

60.21. The Influence of Scientific Policy

The **object of study** also depends on the **objective pursued by scientific policy**. This in turn depends on:

- The **magnitude of the ideals** being pursued.
- The **political-ideological orientation** of scientific policy.
- Concrete decisions such as sample size, object of study, and the criteria for critical reason in hypothesis testing.

Thus, the framing of normality is inseparable from the broader **epistemological and political context** in which science operates.

60.22. Equality of Opportunities as a Model of Normality

In studies of equality of opportunity, the guiding ideal is that, whether in universes of subjects or of limited options, all empirical probabilities converge equally on the theoretical probability, 1/N.

Such models are closest to the traditional concept of normality. For example:

- In education, if a new teaching method is applied to a group of students, the ideal outcome is that all students show improvement in performance equally.
- In terms of traditional statistics, this would appear as an equal increase in direct scores across all students.
- In terms of the Second Method, this would mean that the empirical probabilities of performance improvements tend toward the theoretical probability (1/N).[In Spain, when I was a student, teachers used to grade our exams on a scale from zero to one. In this scenario, if most of the students clustered around the grade of one, their empirical probabilities would approximate 1/N within a margin of error. Only those students with outstandingly high or exceptionally low marks would display a significant positive or negative bias at the extremes.]

60.23. Positive Bias Studies

Positive bias studies occur when, in a sample of N, **one subject or option stands out as more ideal than the rest**.

For example, in a multiple-choice questionnaire on ecological attitudes, where each question offers several items but only one represents the “ideal” (i.e., the most ecological response), the ideal outcome is that this single option accumulates the majority of frequencies.

- The ideal response should tend toward the **Maximum Possible Empirical Probability** (probability = 1).
- All other responses should tend toward **Minimum Possible Empirical Probability** (probability = 0).

Similarly, in a test situation, the correct option should dominate in frequency over incorrect ones.

60.24. Positive Bias in Universes of Subjects

In universes of subjects, a positive bias study would mean that, for whatever reason, **one subject rises above the others**, accumulating the greatest positive bias. The ideal outcome is again that this subject's empirical probability tends toward 1, the maximum possible.

This establishes a framework where the recognition of excellence, superiority, or ideal performance is systematically modeled.

60.25. Negative Bias Studies

Negative bias studies occur when the ideal outcome is for non-ideal subjects or options to maximize their **negative bias**, i.e., to approach probability zero.

For instance, in the study of a new medicine to reduce symptoms of a disease:

- The ideal result is that, as treatment progresses, the **empirical probability of symptoms per patient** decreases.
- As this probability tends toward zero, the **effectiveness of the medicine** proportionally increases.
- Rational critique accepts a margin of error, acknowledging uncontrolled variables (e.g., patient-specific conditions, side effects, or stochastic biological variations).

Thus, negative bias studies highlight how **success is measured by the suppression of undesirable outcomes**.

[This example of negative bias—where the ideal is a sample of zeros, meaning that all patients succeed in their fight against their condition and ultimately present zero symptoms, with probability zero for each patient—represents a special case within the theory of *Impossible Probability*.]

60.26. The Paradox of Impossible Events as Normal

While in traditional statistics (also called **normal statistics**) the occurrence of impossible events (probability = 0) would be the ultimate definition of abnormality, Impossible Probability turns this notion on its head.

In Impossible Probability, in infinite universes where N tends to infinity and all probabilities tend toward zero, the **normal state** is precisely that **impossible events occur**.[Since I have been living in London, I have constantly witnessed things that would have been absolutely impossible in Spain. What once seemed impossible there has become part of my daily routine here in London.]

Thus, the very phenomenon that would be "abnormal" in classical statistics becomes **normal** in Impossible Probability. This paradox demonstrates the radical redefinition of normality within the theory.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 1 June 2013,
Rubén García Pedraza
imposiblenever@gmail.com